



DOES FOREST DISTURBANCE MATTER FOR CLIMATE DEGRADATION? EVIDENCE FROM TOP ASIAN ECONOMIES

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Abstract. The main purpose of this study was to examine the relationship between forestry and climate degradation in the modern era. Specifically, the study aimed to examine how forest areas are influencing environmental degradation. Given the inevitable link between forests and carbon dioxide (CO₂), the current study focused on examining the impact of changes in forestry on the levels of CO₂ emissions in top Asian economies, including China, India, Indonesia, Malaysia, and Thailand. To this end, the current study was quantitative in nature and utilized advanced methodology such as econometrics of quantile-on-quantile (Q-Q) regression to investigate the forests-environmental degradation link. In particular, we examined the effect of quantiles of forest areas on the quantile of climate change in top Asian economies using the time series data from 1990 to 2018. The findings confirmed that forest areas have a negative and significant impact on climate degradation in the majority of the groups of quantiles for all countries. Therefore, this study highlights the importance of forests in controlling environmental degradation in Asian economies. Lastly, the study recommends the respective government bodies to intervene and provide assistance in environmental initiatives to improve forestry levels.

Keywords: forestry, climate degradation, Asia, quantile-on-quantile regression.

JEL Classification: Q23, Q54, Q56.

Introduction

Maintenance of natural habitats is crucial for ensuring stability in environmental conditions. Currently, there exist amplified environmental threats which disrupt the notion of sustainable economic development. The rising dependence of countries on energy-intensive industries is the key factor in environmental degradation culminating in global warming. The negative

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consequences of greenhouse gas concentration in the atmosphere manifest themselves as severe weather conditions, such as heat waves, droughts, hurricanes, and so forth. Hence, preserving environmental habitats is crucial for economic development and human survival. The seminal work by Werner (1787), who laid the foundation of early geology, discussed the Earth's origin (Chena et al., 2020; Cómbita Mora, 2020; Espinosa-Espinosa et al., 2020; Sorokhtin et al., 2011). Basic research concerning the Earth revealed that, during a certain period, it was inhabitable due to high temperatures. Later, as temperatures decreased, first signs of life emerged. Natural resources provide sustainability along with economic benefits to human civilization. In a similar context, forestry is crucial for climate protection. It was found that 25% of all greenhouse gas emissions emerge in the course of deforestation (Beaty, 2019; Bennett, 2017; Niu et al., 2020; Shahbaz et al., 2019). Hence, in order to alleviate the damaging impact of global warming through greenhouse gases, forests hold the eminent position for storing sufficient levels of carbon dioxide (CO₂). This is because forests are an important source of oxygen which consumes and holds CO₂ and because of photosynthesis, which consumes CO₂ and can control global warming.

The total global forest area amounted to 4 billion hectares, which represented 30.3% of the total land. However, as people started living in settlements, the process of industrialization, deforestation increased in magnitude and had several harmful effects on forests (Zon, 1920), which intensified as technology progressed. The Food and Agriculture Organization defines deforestation as “radical removal of vegetation to less than 10% crown cover” (Delacote, 2012). A recent report published by the Food and Agriculture Organization of the United Nations (2018) assessed global forest resources covering the last 7 decades, that is, from 1948 to 2018. The report revealed that challenges in curtailing deforestation and declining forest acreage remained a problem throughout modern human history. Deforestation for increasing human demands, whether for food or industrial materials, added towards the troubles facing humanity (FRO's, 2018). In the same vein, Curtis et al. (2018) shared eye-opening facts about forest disturbance (2001–2015) by mentioning that “commodity-driven deforestation” was responsible for a massive 27±5%. The authors also highlighted that factors responsible for tree loss during the same time included shifting agriculture, wildfire, and urbanization. Similarly, Delacote (2012) drew attention to the fact that the deforestation rate is higher in developing as compared to developed countries. Thus, he suggested that although such activities contribute towards catastrophes at the global level, the scale and size of their impact is far worse in the developing world (Yang & Grigorescu, 2017).

As a result of growing economic activities, climate change is more evident than ever, in particular in climate differences between urban and rural areas. Zhan et al. (2013) cite lack of greenery, more numerous concrete buildings, and high levels of pollution as few of the causes behind rising temperatures in urban areas. The aftermath of climate change manifests itself in extreme heat waves, water and food shortages, and so forth. Climate change has also impacted R&D activities which, consequently, affect economic growth (Banelienė & Melnikas, 2020). Considering the above, the work of Seymour and Busch is worth mentioning (2016). They argued that deforestation and climate change together subsequently lead to poverty. A large part of their argument was based on the notion of vulnerability; the more vulnerable the population, the less they are able to withstand the impact of any disaster. The impact of

deforestation and climate change on vulnerable nations can easily be observed. Countries like India, Pakistan, Indonesia, and Brazil have experienced human suffering due to climate change (Eckstein et al., 2019). For example, extreme heatwaves increased the number of storms and floods became much more frequent. In the backdrop of all these challenges, researchers like Chazdon and Brancalion (2019) are warning the entire global community about grave threats to our ecosystem. They suggest that the strategy of forestation must be adopted against challenges like climate change.

Thus, the main purpose of this study was to examine the current relationship between forestry and climate change. Specifically, the study examined how the present disturbance in forest areas influences environmental degradation. Given the inevitable link between forests and CO₂, the current study focused on the impact of changes in forestry on the levels of CO₂ discharge in top Asian economies, including China, India, Indonesia, Malaysia, and Thailand. Notably, the current literature on forestry lacks empirical examinations. Hence, there is a shortage of inclusive and quantitative links among the variables of interest. Thus, the present study was quantitative in nature and utilized an advanced methodology to investigate the forests-environmental degradation link by using the econometrics of quantile-on-quantile (Q-Q) regression. The Q-Q approach involves a comparison of quantiles and an integration of quantile regression with nonparametric estimation (Sim & Zhou, 2015). Evidence from the literature on urbanization, climate change, and tourism supports the use of the Q-Q approach (Abbas et al., 2019; Shahzad et al., 2017; Shastri et al., 2015). Wang's (2012) work is also worth mentioning, as it showed that the relationship between variables is nonlinear in nature, and any application of linear relation can possibly fail to provide an accurate picture. Based on this and the present scenario of forestry and climate change, the Q-Q approach could prove to be the most effective. This approach can reveal the true nature of relationships among variables, as well as any complexities that exist between forestry and climate change, which would be overlooked in evaluations through traditional methods.

1. Literature review

A balanced natural habitat is vital to protect against global warming. Forests hold an eminent position to mitigate the detrimental effects of climate change, along with providing other benefits such as livelihood for people, habitat for animals, a safeguard from watersheds, and reduced soil erosion. Hence, forest disturbance is a critical issue in environmental literature. A review of previous studies suggests that deforestation in the process of human mobility is leading to climate change, one of the serious challenges of the modern world (Al-Blooshi et al., 2020; Al-Husseini, 2020; Al-Tufaili, 2020; Yao et al., 2015). The Business Continuity Institute reports (2012, 2013, 2014, 2016, 2017, 2018) confirmed an increased number of regularly occurring natural disasters. Similarly, Pace et al. (2015) reported an increased frequency of natural disasters. Borrowing the reference of the Intergovernmental Panel on Climate Change (Agrawala, 1998), Yao et al. (2015) sees the human role behind increased global warming, which is duly supported by studies like Kalnay and Cai (2003) and Zhang et al. (2010). They point out that human activities, such as an increased transformation of forests for agricultural purposes, are triggering worst-case scenarios such as global warm-

ing. Furthermore, the literature indicates that early stages of economic development lead to greater pollution levels where a reversal of trends is observed at higher stages of development (Lapinskienė et al., 2014). In the current environmental era, owing to the significance of natural resources for climate change, the role of forestry is considered crucial, especially with regards to its link with CO₂ emissions (Smith et al., 2020).

Among others, Baccini et al. (2012) studied the link between CO₂ emission and forestry by focusing on improved methods to estimate CO₂ density resulting from deforestation. They found that deforestation restricts the ability to absorb CO₂. In consequence, it is then emitted into the atmosphere. Moreover, criticizing the accuracy of the estimates reported in conventional data sources, the authors reported that Indonesia and Brazil alone are responsible for 35% of CO₂ resulting from deforestation. The study urges all the tropical countries to utilize improved data for measuring CO₂ from deforestation and the above-ground biomass to effectively correspond to rising environmental challenges.

Similarly, Van-der-Werf et al. (2009) reported that, after fossil fuel combustion, the second most vital cause of CO₂ emission in the atmosphere is deforestation. They found that deforestation rate is decreasing, leading to CO₂ emissions decreasing by 30%. Moreover, the authors noted forest disturbance in tropical peatlands are be a crucial source of CO₂ emission. In another study, Repo et al. (2011) analyzed indirect CO₂ emanation from bio-energy generated from forest harvest residues. They argued that utilizing forest harvest residues lowers the forest CO₂ emissions by leaving the lower stock to burn and decompose. Analyzing the forests in Finland, the authors reported that harvest combustion causes indirect CO₂ emission in the process of producing bio-energy. However, these indirect emanations per unit of energy fell gradually, from a level initially equivalent to that of fossil fuel combustion to that approaching natural gas combustion (Chen & Gao, 2020; Chen et al., 2020a; Khvatskaya et al., 2020; Kim et al., 2020; Malkin et al., 2020; Mutascu, 2014).

Furthermore, Rowntree and Nowak (1991) examined the link between CO₂ emissions and forests in the urban areas of the United States. They found that US urban forestry holds 800 million tons of carbon. Moreover, urban forests not only store carbon over the years, but also lower CO₂ emissions through cooling ambient air along with enabling the inhabitants to curtail yearly heating and cooling. McPherson (1998) also studied the role of forests in environmental protection by analyzing the role of urban forests in controlling CO₂ emissions. He found that urban forests lowered emission levels both directly and indirectly in the Sacramento County region. First, CO₂ emission into the atmosphere was reduced by eight million tons through the direct storage capacity of urban forests comprising of six million trees. Secondly, the presence of urban forests also lowers the need for expending energy on heating and air-conditioning, thereby cutting emission by over seventy-five thousand tons (Grdic et al., 2019).

In China, Zhao et al. (2010) inspected the role of forests in lowering atmospheric CO₂ emissions. They utilized the data for urban forests in Hangzhou province along with the energy usage data of several mining and manufacturing industries. The study, similar to McPherson (1998), found that urban forests play a crucial part in reducing CO₂ density in the atmosphere. Specifically, the results documented that urban forests stored 12.9 million tons of carbon and sequestered carbon by 1.3 million tons. Moreover, the study also re-

ported that forest sequestration in urban areas led to a counterweight equivalent to 18.5% of industry CO₂ emissions. However, urban forests hold CO₂ comparable to 1.75 times of the emissions of industries in Hangzhou province.

In another study, Malhi and Grace (2000) examined the link between tropical forest and its potential for reducing atmospheric CO₂ emissions. Similar to the studies of Baccini et al. (2012) and Van-der-Werf et al. (2009), they confirmed the significance of tropical forests in absorbing and storing CO₂ emissions to prevent their detrimental effects on the environment. Utilizing improved estimates, Houghton (1991) also contended that tropical deforestation is damaging for climate change. In a similar study, Cramer et al. (2004) found that the deforestation rate is increasing the indeterminate impact of atmospheric CO₂ emissions. The authors found that, given the increasing deforestation, the CO₂ emissions in the 21st century range between 101 to 367 gigatons. In addition, deforestation also harms the environment by increasing temperature and decreasing rainfall. Amiro et al. (2010) also analyzed the impact of forest disturbance on CO₂ emissions in America. Their results stated that CO₂ loss from forest disturbance is highly evident especially in Florida. Similar results were reported by Hollinger et al. (1998) while examining forests and CO₂ emission in Siberia.

Studying Amazon forests, Bullock et al. (2020) also identified deforestation as an important cause of environment degradation (which is also supported by other researches, Grdic et al., 2019; Smith et al., 2020). However, based on the findings of Wang (2012), the study explained that the relationship between the variables is nonlinear in nature, and any application of linear relations can possibly fail to provide a true picture. Therefore, based on this and the present scenario of forestry and climate, the change relations Q-Q approach could prove to be the most effective. This approach can reveal the true nature of the relationship among variables. In addition, this approach can also unveil any complexities that exist between forestry and climate change, which would otherwise be left unattended in case of evaluation through traditional methods.

2. Methodology

The aim of the current study was to inspect the nonlinear impact of forest areas on CO₂ emission of top Asian economies (China, India, Indonesia, Malaysia, and Thailand), which have the highest forest land area in the Asian region. To this end, the current study utilized land (measured in square kilometers) as a measure of forest areas. The per capita of CO₂ emission was taken as an index of environmental degradation, and was estimated in metric tons per capita. The study used World Bank data from 1990 to 2018.

Below follows a description of the Q-Q approach. It generally involves comparisons between two probability distributions made by plotting their quantiles against each other (Chen et al., 2020b; Sim & Zhou, 2015). Some current researchers approach the Q-Q method in a generic sense and believe it to be based on quantile regression and nonparametric estimation. The quantile regression methodology was widely acknowledged by researchers after it was developed and shared in the seminal work of Koenker and Bassett (1978). It was seen as an advancement of the classical linear regression model. The unique feature that differentiates quantile regression analysis from ordinary least squares (OLS) estimation is its ability to

analyze the detailed impact of the independent variable on the dependent variable. Namely, it examines the central as well as the tail part of the dependent variable distribution. In addition, the feature of local linear regression also differentiates quantile regression from OLS estimation, as it details the local effect of the independent variable quantiles on the dependent variable. The rationale of researchers like Stone (1977) and Cleveland (1979) behind this method was to create a fit of linear regression with the data points in the neighborhood in a sample, that is, allocating more weight to the proximal data points. Such a feature of the combination of approaches makes quantile regression more informative than alternatives like OLS. The current study considered the impact of forestry land on national CO₂ emissions, which was measured by determining the quantile effect of forestry on the quantile effect of national CO₂ emission. Thus, the quantile regression model for the current study was:

$$CO2_t = \beta^\theta (FOR_t) + \mu_t^\theta. \quad (1)$$

In this model, CO₂_{*t*} stands for CO₂ emissions, that is, the proxy of environmental degradation of a country in the time period *t*. In the same vein, FOR_{*t*} denotes the forest land in a specific country in a time period *t*. *q* refers to the quantile of the conditional distribution of the per capita CO₂ emission (CO₂_{*t*} in the current model). Further, the model also includes the error term U_t^θ which is zero (conditional *q*th quantile). Further, as the relevant information regarding the link between forest land and CO₂ emission was unavailable, β^θ was also included in the model as an unknown function.

It is worth highlighting the model's flexibility despite the absence of any proposition concerning the nature of the relationship between forest area and CO₂ emission. Apart from such features, there are areas of concern regarding quantile regression. One such area is the model's ability to take into account the impact of forestry shock on the relationship between forest areas and environmental degradation. By way of illustration, if there is a high increase in forest land, then this positive impact will be different from the minor positive increase in forest land on the relationship between forests and environmental degradation. Furthermore, the nature of the shock need not be similar to forestry shock, whether it be negative or positive.

Next, the relationship between the Theta quantiles of the exploratory and explanatory variables is examined in the neighborhood of explanatory variables (FOR^τ) by using local linear regression. As the β^θ value was unknown in this case, the first-order Taylor expansion was applied on quantile FOR_{*t*} for estimation.

$$\beta^\theta (FOR_t) \approx \beta^\theta (FOR^\tau) + \beta^{\theta'} (FOR^\tau) (FOR_t - FOR^\tau). \quad (2)$$

In Eq. (2), the β^θ which represents the partial derivative of the variable FOR_{*t*} in reference to FOR is generally regarded as the slope when it comes to the linear regression model. An overview of the previous equation further highlights that parameters like $\beta^\theta (FOR^t)$ and $\beta^{\theta'} (FOR^t)$ are double indexed by θ and *t*. Further, the equation suggests the parameters and their functions. For instance, in Eq. (2), parameters like $\beta^\theta (FOR^t)$ and $\beta^{\theta'} (FOR^t)$ are functions of θ and FOR^{*t*} whereas FOR^{*t*} is the function of *t*. Hence, it can be said that $\beta^\theta (FOR^t)$ and $\beta^{\theta'} (FOR^t)$ are functions of θ and *t*. Based on this, the parameters $\beta^\theta (FOR^t)$ and $\beta^{\theta'} (FOR^t)$ could be written as $\beta_0(\theta, t)$ and $\beta_1(\theta, t)$. Therefore, this equation could be written as:

$$\beta^\theta (FOR_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(FOR_t - FOR^\tau). \tag{3}$$

By incorporating Eq. (3) in Eq. (1), the following equation will emerge:

$$CO2_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(FOR_t - FOR^\tau)}_{(*)} + \mu_t^\theta. \tag{4}$$

Examination of Eq. (4) indicates the θ th conditional quantile of CO2 emanation which in this equation is depicted as (*). This part of the equation shows the relationship between θ th conditional quantile of the CO2 emanation with the forest land (t^{th} quantile); as indicated previously in the model, β_0 and β_1 are indexed by both θ and t . Furthermore, these parameters may vary at θ and t quantiles and an assumption of a linear regression between them will not always be true. Therefore, one may conclude that Eq. (4) is suitable to estimate the dependence between these variables by examining the dependence amongst the distribution of these variables.

In order to estimate Eq. (4), it is essential to use the new estimated values represented by \widehat{FOR}_t and \widehat{FOR}^τ instead of the earlier values FOR_t and FOR^τ . In the same vein, the following minimization problem will be used to estimate the parameter (b_0 and b_1) for β_0 and β_1 .

$$\min_{b_0, b_1} \sum_{i=1}^n \rho_\theta \left[CO2_t - b_0 - b_1 \left(\widehat{FOR}_t - \widehat{FOR}^\tau \right) \right] \times K \left(\frac{F_n \left(\widehat{FOR}_t \right) - \tau}{h} \right). \tag{5}$$

Therefore, Eq. (5) includes $\rho^\theta(u)$, I and K, which represent quantile loss function, indicator function, and Kernel function respectively. The current study implemented the Gaussian Kernel function (GKF) based on its ease of use and efficiency to weigh observations in the proximity of \widehat{FOR}_t . GK is symmetrical, therefore the outliers have lower values. The opposite can be observed in the relationship between weights and distribution of functions \widehat{FOR}_t and \widehat{FOR}^τ .

In order to use non-parametric estimation techniques, several elements are of critical importance, like bandwidth choice (Hussain et al., 2020). Its importance lies in its ability to identify the neighborhood size around the target point, which ensures the smoothness of estimates. Apart from this, the justification for the choice of bandwidth is dependent on creating an equilibrium between bias and variance which are the results of large and small bandwidth. The current study implements the findings of Sim and Zhou (2015) and uses a bandwidth parameter of 0.05.

3. Data analysis and interpretation

To apply the quantile-on-quantile approach, the yearly information was changed into quarterly using the quadratic match sum strategy, as recommended by Shahbaz et al. (2018), Mishra et al. (2019), and Batool et al. (2019). This technique is useful while changing low recurrence information into high recurrence information, as it permits to deal with start to end deviation in the dataset (Shahbaz et al., 2018; Mishra et al., 2019; Sharif et al., 2019a). In the subsequent stage, we used the descriptive measurements to explain the layout of both variables for all countries and the results are shown in Table 1.

Table 1. Results of descriptive statistics (source: authors estimation)

Descriptive	China	India	Indonesia	Malaysia	Thailand
Panel A: Forestry Land (Square Kilometer)					
Mean	1.849	0.671	1.008	0.218	0.159
Minimum	1.571	0.639	0.903	0.208	0.140
Maximum	2.098	0.708	1.185	0.223	0.170
Std. Dev.	0.170	0.024	0.0823	0.004	0.007
Skewness	4.134	3.198	2.752	3.657	5.316
Kurtosis	1.610	1.472	2.419	2.204	3.837
Jarque-Bera	22.254	14.802	17.924	26.545	8.578
Probability	0.000	0.000	0.000	0.000	0.014
Panel B: Carbon Dioxide Emission					
Mean	4.421	1.127	1.520	6.192	3.345
Minimum	2.152	0.709	0.824	3.139	1.606
Maximum	7.557	1.728	2.564	8.130	4.620
Std. Dev.	2.059	0.321	0.439	1.428	0.897
Skewness	3.469	4.546	2.695	4.387	3.375
Kurtosis	1.578	1.904	2.906	2.194	2.058
Jarque-Bera	13.267	12.695	16.183	14.404	10.632
Probability	0.000	0.000	0.000	0.000	0.000

The discoveries of descriptive statistics demonstrate that the mean estimation of a considerable number of factors is positive for forest land. The highest value for forest land is the case of China, which is 1.849 million square kilometers, trailed by Indonesia 1.008 million square kilometers and India 0.671 million square kilometers. Thailand and Malaysia had the smallest forest areas, with 0.15 and 0.218 million square kilometers respectively. However, the mean values for per capita of carbon emanation are positive for all nations. The largest estimate is for Malaysia which is 6.192 metric tons per capita, followed by China 4.421 per capita of metric tons, and Thailand 3.345. The least value is shown on account of Indonesia and India which are 1.520 and 1.127, respectively. The discoveries likewise showed the estimation of kurtosis, and it is seen that the value is more noticeable than 3 in all nations which shows the proximity of nonlinear connection between the factors. In addition, the normality of the factors was checked utilizing the Jarque-Bera (JB) test. The discoveries of the JB test affirm the dismissal of the null of normality. The outcomes affirm that FOR and CO₂ emanation have a nonlinearity in all countries. In this manner, this spurs us to use distinctive quantiles estimations since these are suitable in the nonlinear regimes (Raza et al., 2018; Troster et al., 2018; Sharif et al., 2019b).

Next, so as to confirm the stationarity characteristics, the present investigation utilized a nonlinear based quantile unit root test to affirm the stationarity characteristics among forest land and CO₂ emanation. The discoveries of the quantile-based unit root test are shown in Table 2. Table 2 demonstrates the constancy parameter and t-stats for forest land and CO₂

Table 2. Quantile unit root test (source: authors estimation)

Quantile	China						India						Indonesia						Malaysia						Thailand						
	FOR			CO2			FOR			CO2			FOR			CO2			FOR			CO2			FOR			CO2			
	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats	$\alpha(\tau)$	$\alpha(\tau)$	t-stats		
0.05	0.912	0.053	0.885	0.885	-0.117	0.840	0.840	-1.420	0.900	-0.266	0.885	0.885	-0.531	0.904	-0.103	0.893	0.893	-0.336	0.891	0.891	-0.227	0.886	0.886	-1.591	0.911	0.911	0.886	0.886	-1.591	0.911	0.911
0.10	0.912	0.159	0.892	0.892	-0.151	0.920	0.920	0.345	0.901	-0.322	0.892	0.892	-1.846	0.912	0.028	0.897	0.897	-1.474	0.896	0.896	-0.750	0.898	0.898	-2.228	0.911	0.911	0.898	0.898	-2.228	0.911	0.911
0.20	0.909	-1.223	0.882	0.882	-2.534	0.903	0.903	-0.918	0.902	-2.218	0.891	0.891	-2.335	0.905	-0.659	0.900	0.900	-1.875	0.906	0.906	-0.458	0.896	0.896	-1.802	0.911	0.911	0.896	0.896	-1.802	0.911	0.911
0.30	0.910	-0.407	0.887	0.887	-2.450	0.897	0.897	-1.745	0.904	-2.352	0.892	0.892	-2.145	0.909	-0.432	0.903	0.903	-1.681	0.902	0.902	-1.188	0.905	0.905	-1.961	0.909	0.909	0.905	0.905	-1.961	0.909	0.909
0.40	0.910	-1.130	0.897	0.897	-1.832	0.898	0.898	-1.551	0.908	-1.402	0.893	0.893	-2.012	0.909	-1.098	0.906	0.906	-1.687	0.901	0.901	-1.793	0.906	0.906	-1.612	0.910	0.910	0.906	0.906	-1.612	0.910	0.910
0.50	0.910	-2.417	0.898	0.898	-2.574	0.897	0.897	-1.435	0.909	-1.033	0.893	0.893	-2.162	0.908	-2.362	0.906	0.906	-1.747	0.901	0.901	-2.167	0.906	0.906	-1.827	0.909	0.909	0.906	0.906	-1.827	0.909	0.909
0.60	0.909	-1.332	0.896	0.896	-2.260	0.895	0.895	-1.461	0.909	-0.956	0.894	0.894	-1.033	0.908	-1.162	0.901	0.901	-1.823	0.900	0.900	-1.798	0.906	0.906	-1.886	0.907	0.907	0.906	0.906	-1.886	0.907	0.907
0.70	0.909	-2.002	0.887	0.887	-2.179	0.892	0.892	-1.743	0.908	-0.972	0.895	0.895	-1.372	0.906	-0.869	0.900	0.900	-1.782	0.900	0.900	-1.719	0.906	0.906	-2.003	0.904	0.904	0.906	0.906	-2.003	0.904	0.904
0.80	0.909	-1.842	0.860	0.860	-1.283	0.873	0.873	-1.804	0.912	0.369	0.896	0.896	-1.520	0.906	-0.654	0.902	0.902	-1.781	0.900	0.900	-1.055	0.896	0.896	-2.125	0.898	0.898	0.896	0.896	-2.125	0.898	0.898
0.90	0.910	-0.105	0.842	0.842	-0.735	0.892	0.892	-0.432	0.914	0.140	0.887	0.887	-1.797	0.891	-0.704	0.897	0.897	-0.731	0.907	0.907	-0.125	0.895	0.895	-0.887	0.809	0.809	0.895	0.895	-0.887	0.809	0.809
0.95	0.903	-0.628	0.787	0.787	-0.963	0.894	0.894	-0.255	0.910	-0.009	0.883	0.883	-0.608	0.886	-0.400	0.893	0.893	-0.502	0.865	0.865	-0.363	0.896	0.896	-0.614	0.692	0.692	0.896	0.896	-0.614	0.692	0.692

emanation in all counties. The discoveries of quantile unit root tests affirm that all factors demonstrate non-stationary characteristics at the level arrangement. In addition, the constancy parameter coefficient is likewise near-zero overall quantiles in all countries proposing non-stationary characteristics at a level series. In addition, the quantile cointegration test was utilized to certify the nonlinear connection among FOR and CO₂ emanation in all top Asian economies. The discoveries are shown in Table 3 using α and δ values. The table additionally revealed three diverse critical value of quantile cointegration at 1%, 5%, and 10% degree of significance. The outcomes asserted that FOR and CO₂ emanation have a strong nonlinear relationship in all selected Asian nations. In this manner, we proceed to evaluate quantile on the quantile approach for long-run coefficients.

The next step involved reporting the results of quantile on quantile regression. The findings are demonstrated in Figures 1 to 5. In the figures, forest land area is placed on the x-axis as an independent variable. CO₂ emission is used as a proxy for climate degradation on the y-axis. The coefficients of both variables are displayed on the z-axis. In the case of China,

Table 3. Results of quantile cointegration test

China					
Model	Coefficient	Supremum norm value	Critical Value at 1%	Critical Value at 5%	Critical Value at 10%
CO ₂ _t vs. FOR _t	α	3321.379	1600.805	1195.121	419.422
	δ	665.760	349.350	195.757	170.767
India					
Model	Coefficient	Supremum norm value	Critical Value at 1%	Critical Value at 5%	Critical Value at 10%
CO ₂ _t vs. FOR _t	α	4489.993	1372.933	750.981	368.660
	δ	1222.007	457.762	272.879	196.615
Indonesia					
Model	Coefficient	Supremum norm value	Critical Value at 1%	Critical Value at 5%	Critical Value at 10%
CO ₂ _t vs. FOR _t	α	2728.819	1794.093	1095.915	735.711
	δ	1600.847	924.807	542.847	236.956
Malaysia					
Model	Coefficient	Supremum norm value	Critical Value at 1%	Critical Value at 5%	Critical Value at 10%
CO ₂ _t vs. FOR _t	α	6158.666	1794.306	1208.645	667.756
	δ	3486.327	1388.385	806.236	419.527
Thailand					
Model	Coefficient	Supremum norm value	Critical Value at 1%	Critical Value at 5%	Critical Value at 10%
CO ₂ _t vs. FOR _t	α	4203.003	2149.095	1533.260	1176.502
	δ	1774.446	1233.564	603.201	368.736

Note: This table presents the results of the quantile cointegration test of Xiao (2009) for the logarithm of the forestry land (FOR) and per capita of carbon dioxide emission (CO₂).

the findings affirmed that the impact of forest land is negative and significant on all groups of quantiles of CO₂ emanation. In fact, the effect is more noticeable on low quantiles (i.e., 0.05–0.40) of forest land and across all quantiles of carbon emanation (i.e., 0.05–0.95). The results further confirm the negative effect of forest land on carbon emanation on the high quantiles of both variables, but the magnitude is low as compared to low forest land. The results moreover suggested that a sharp boost of climate degradation is because of the reduction of forest land in the country. In summary, the findings confirm a significant negative impact of forest land on climate degradation in China.

The effect of forest land on climate degradation is also significant, as well as interesting, in the case of India. The findings confirmed that the influence of forestry on climate degradation is noteworthy in all combinations of different quantiles between both variables. The results suggested a mixed result in the case of India. The effect of forest land is positive and significant on the low quantiles of forest land (i.e., 0.05–0.50) and all quantiles of climate degradation (i.e., 0.05–0.95). These results suggest that low forest land increases climate degradation

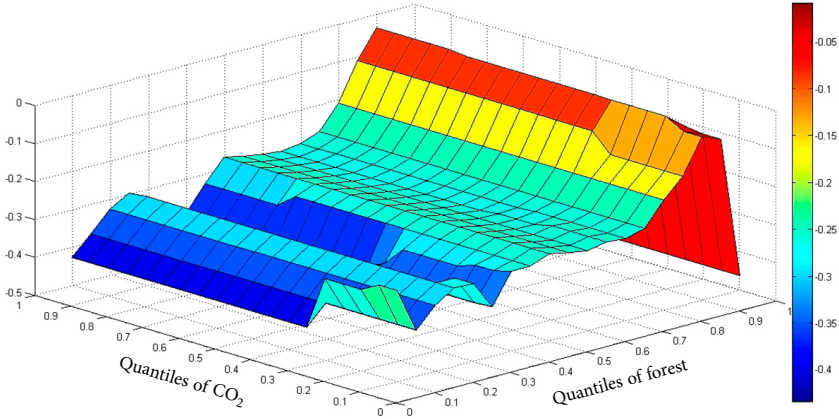


Figure 1. Quantile on quantile regression estimation for China

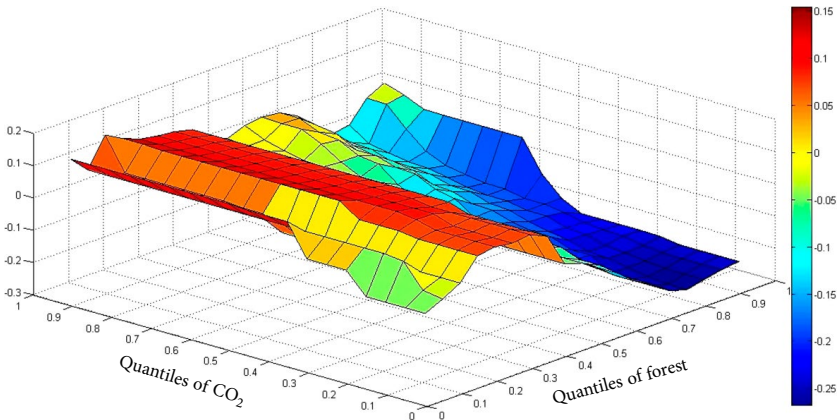


Figure 2. Quantile on quantile regression estimation for India

in the Indian economy. However, the findings further confirmed that the effect of forest land (on high quantiles, i.e., 0.50–0.95) is negative and significant on climate degradation (all quantiles, i.e., 0.050–0.95). Technically speaking, the outcomes confirmed that small forest land area has a positive impact on climate degradation; however, large forest land area has a negative and significant impact on CO₂ emanation in the Indian economy. Therefore, the findings confirm that more forest land will help to control climate degradation in the Indian economy.

In Indonesia, the effect of forest land on climate degradation is also significant but weak and negative in the majority of the grouping of quantiles. The findings of Q-Q affirmed that effect is positive on the low quantiles of forest land (i.e., 0.05–0.35) and low to lower-middle quantiles of CO₂ emanation (i.e., 0.05–0.55). This confirmed that small forest land area increases the CO₂ emanation. However, the effect is negative and significant on the high quantiles of forest land (i.e., 0.85–0.95) and low quantiles of CO₂ emission (i.e., 0.05–0.25). In simpler terms, the effect of forest land is negative and significant on carbon emanation across almost all quantiles distribution.

In Malaysia, the effect of forest land on climate degradation is also significant and strongly negative in a majority of a grouping of quantiles. The discoveries of Q-Q declared that effect is positive on the low quantiles of forest land (i.e., 0.05–0.35) and middle to upper-middle quantiles of CO₂ emanations (i.e., 0.40–0.80). This stated that the small forest land area surges the CO₂ emanation. Opposingly, the influence is negative and significant on the high quantiles of forest land (i.e., 0.75–0.95) and low quantiles of CO₂ emission (i.e., 0.05–0.25). Generally, the influence of forest land is negative and momentous on carbon emanations in almost all quantiles distribution.

In the case of Thailand, the results acknowledged that the influence of forest land is negative and substantial on all combinations of quantiles of CO₂ emanations. Relatively, the influence is more perceptible and positive on low quantiles (i.e., 0.05–0.15) of forest land and low quantiles of carbon emanation (i.e., 0.05–0.55). The results further confirm a negative influence of forest land on carbon emanation on the high quantiles of both variables, the outcomes of Q-Q confirmed that the influence of forest land is negative on climate degradation on the upper-middle quantiles (i.e., 0.60–0.85) of both variables. The results moreover recommended that a strident boast in climate degradation is because of the dropping of forest land in the country. In general, the findings confirm a significant negative impact of forest land on climate degradation in Thailand, as well.

In the final stage, the current study applied the Granger causality test in the quantiles approach suggested by Troster et al. (2018). This approach was applied to examine the causal connection between forest land area and carbon emanation in top Asian countries. In particular, we investigate the change of forest land area does Granger cause on the change of climate degradation. The results are reported in Table 4. The findings confirm a bidirectional causal connection between forest land and climate degradation in the case of China, India, and Malaysia. In these countries, the causality is running from climate degradation to forest land and from forest land to climate change. However, we found a uni-directional causal connection in the case of Indonesia and Thailand. The results confirmed that causality is running from forest land (climate degradation) to climate degradation (forest land) in the case of Indonesia (Thailand).

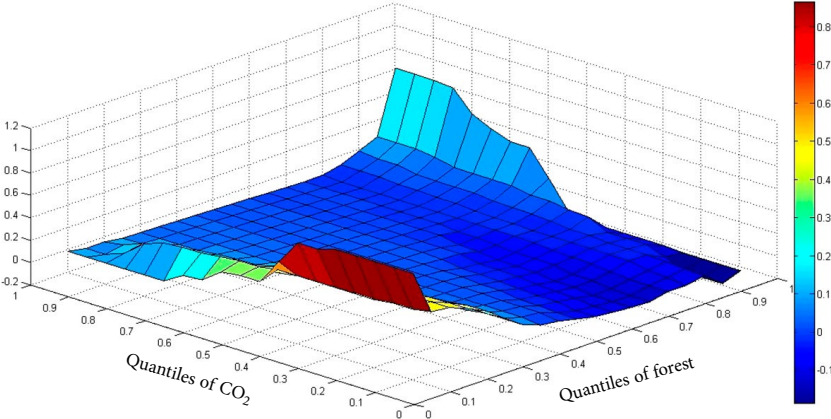


Figure 3. Quantile on quantile regression estimation for Indonesia

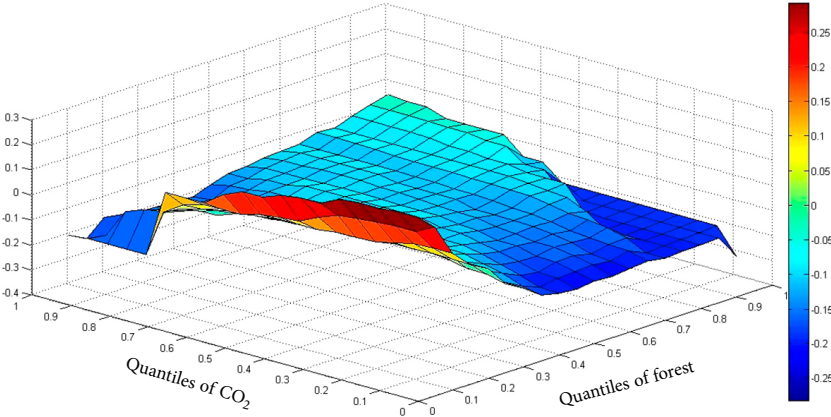


Figure 4. Quantile on quantile regression estimation for Malaysia

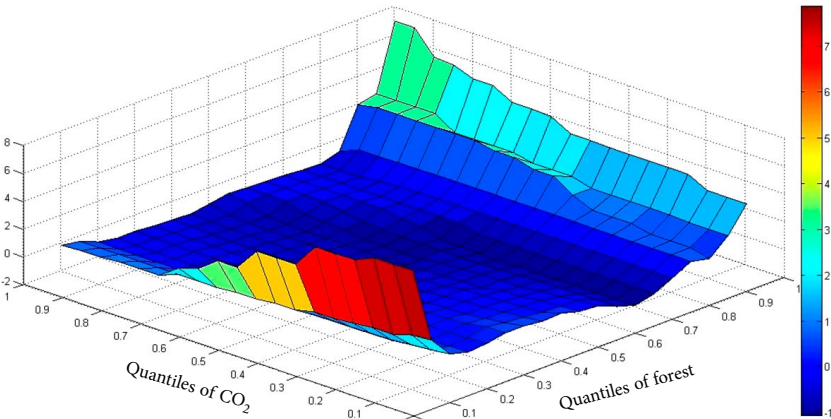


Figure 5. Quantile on quantile regression estimation for Thailand

Table 4. Granger causality in quantile test results (source: authors estimation)

China												
	All Quantiles	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
ΔFOR_t to ΔCO_2_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔCO_2_t to ΔFOR_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
India												
ΔFOR_t to ΔCO_2_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔCO_2_t to ΔFOR_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Indonesia												
ΔFOR_t to ΔCO_2_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔCO_2_t to ΔFOR_t	0.483	0.194	0.268	0.468	0.754	0.831	0.641	0.502	0.442	0.382	0.327	0.242
Malaysia												
ΔFOR_t to ΔCO_2_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔCO_2_t to ΔFOR_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Thailand												
ΔFOR_t to ΔCO_2_t	0.295	0.948	0.893	0.857	0.642	0.521	0.702	0.782	0.848	0.882	0.902	0.973
ΔCO_2_t to ΔFOR_t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Discussion and conclusion

The rising dependence of countries on energy-intensive industries is the key factor for environmental degradation which results in global warming. The negative consequences of the concentration of greenhouse gases in the atmosphere can be observed in extreme weather conditions including heat waves, droughts, hurricanes, etc. Hence, the preservation of environmental habitat is crucial for economic development and human survival. Furthermore, the need for sustainable development has resulted in deployment of space technologies to support development goals including eradication of poverty as well as sustainability of the environment (Roggeri et al., 2011; Aleem, 2020; Alhbaby, 2020; Ali et al., 2020; Yun, 2020; Janssen, 2020; Hornung, 2020). Past literature which laid the foundation of early geology discussed the Earth's origins. This fundamental knowledge about the Earth revealed that it was once inhabitable because of high temperatures. Later, as it cooled down, the signs of environment and life emerged. The role of natural resources is important for preservation along

with the economic benefits to human civilization. In a similar context, the role of forests is crucial for climate protection. It is found that 25% of the entire greenhouse generation is originated in the course of deforestation. Given the inevitable link between forests and CO₂, the current study is focused on examining the impact of changes in forestry on the levels of carbon discharge in top Asian economies, including China, India, Indonesia, Malaysia, and Thailand. In response, the current study is quantitative in nature that utilized the advanced methodology to investigate forest-environmental degradation link by using the econometrics of Q-Q regression. The findings confirm that forest land has a negative and significant impact on climate degradation in all top Asian countries. The results further suggested that small forest land increases the carbon emanation; however, the highest forest land area helps to reduce the carbon emanation in top Asian economies.

Based on the findings of the study, it is recommended that the governments of the aforementioned countries managed their forest areas in order to control climate degradation. First of all, it is necessary to implement legislation which would preserve forests and natural resources. This will help maintain balance between sustainability and environmental degradation. Secondly, governments need to take initiative to implement eco-friendly solutions, according to which trees will be planted by both governments and households. Thirdly, governments need to raise awareness among the general population regarding forests and the possible adverse effect which may arise due to their degradation. Fourthly, governments need to extend their support in providing fertilizes and other necessary materials which will help the general public engage in environmental initiatives. Lastly a partnership between public and private sectors is needed, where environmental initiatives would be tackled jointly through collaboration.

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