Article

Is Shrimp Farming in Thailand Ecologically Sustainable?[*]

Toyokazu Naito
Department of Economics
Kyoto Gakuen University, Japan
naito@kyotogakuen.ac.jp

and

Suphakarn Traesupap
Coastal Development Centre
Faculty of Fisheries
Kasetsart University, Thailand
kajikawas@hotmail.com

Abstract

Shrimp farming in Thailand is considered to be one of the main causes of mangrove deforestation. The Environmental Kuznets Curve (EKC) hypothesis, however, posits that economic development eventually reverses resource degradation. This hypothesis is examined using pooled data on mangrove loss and Gross Provincial Product (GPP) from 23 provinces in Thailand in various years between 1975 and 2004. The empirical results show strong evidence of an EKC relationship between mangrove loss and GPP. In addition, the relationship between shrimp farming and mangrove loss is examined. Shrimp farming is found to significantly affect the extent of mangrove deforestation. The development of extensive and semi-intensive shrimp farming techniques quickens mangrove deforestation, but intensive shrimp farming, which developed during the 1990s, reduces mangrove loss.

Keywords: environmental Kuznets curve, extensive and intensive shrimp culture, mangrove deforestation

1. Introduction

As an economy develops, a society's wealth increases; at the same time, the environment becomes polluted and the resources are depleted. During the 1970s and 1980s, the shrimp farming industry in Thailand developed rapidly and income levels rose drastically; however, many mangrove forests were cut down to create pond habitat for shrimp farming. In the 1990s, mangrove deforestation in Thailand became a major concern in Japan, one of the main importers of shrimp products from Thailand. Will mangrove deforestation continue or will the forests recover as Thailand's economy continues to develop?

The relationship between economic development and environmental degradation has been a concern among environmental economists since the 1970s, and the discussion has been framed within the "Environmental Kuznets Curve (EKC)" hypothesis since the 1990s. The EKC hypothesis posits that environmental degradation and resource destruction increase in the early stages of economic development but eventually decline as the economy develops and per capita income increases. The origin of the EKC hypothesis is the so-called "Kuznets Curve," in which Kuznets (1955) postulated that the relationship between the extent of income inequality and the level of income can be represented in an inverted-U shape. Thus the EKC hypothesis is also called the "inverted-U" hypothesis, with environmental degradation represented on the vertical axis and the level of per capita income on the horizontal axis.

Although no study exists that focuses on the EKC relationship between mangrove deforestation and income level, there are a number of studies dealing with the EKC hypothesis and deforestation in the literature. In those studies, the existence of the EKC relationship between deforestation and income level has been demonstrated empirically (Antle and Heidebrink, 1995; Cropper and Griffiths, 1994 ; Koop and Tole, 1999; Lopez and Galinato, 2005; Panayotou, 1993; Shafik, 1994a; and Shafik and Bandyopadhyay, 1992)[1]. These studies show that if a society becomes rich, the forest that has been destroyed eventually recovers.

Some of these studies have estimated an EKC turning point in which economic development eventually reverses forest degradation. Those estimated EKC turning points exist between $5000 and $8000 (1985 US$ level) (Barbier and Burgess, 2001; Bhattarai and Hammig, 2001; Cropper and Griffiths, 1994; Koop and Tole, 1999; and Lopez and Galinato, 2005), income levels that are far beyond the per capita income of the countries possessing tropical forests. Therefore, there is no guarantee that current deforestation will be reduced by an increase of per capita income, as the EKC hypothesis suggests. According to one future prediction, even if the income level reaches the EKC turning point in the future, this turning point may be reached too late for forests to recover from deforestation.

In this study, we first examined the existence of the EKC relationship in the particular case of mangrove deforestation. We used pooled data on mangrove-covered area, Gross Provincial Product (GPP), provincial population, and provincial shrimp farming production

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[1] The existence of the EKC hypothesis has been empirically shown in the literature; however, it should be noted that these results depend on the data used (cross-country data, panel or pooled data, or a single country's data); estimation models used (equation form, explained variable used, or explanatory variables used); and estimation methods used (one point fixed model, fixed effect model, or random effect model).

from 23 provinces in Thailand with mangrove forests during various years between 1975 and 2004. If evidence of the EKC relationship was convincing, then we examined the possible determinants of the EKC relationship and analyzed their impact on the EKC relationship.[2] In general, mangrove deforestation has been attributed to increased demand for land due to population growth and economic development in Thailand. Therefore, by using the population growth rate as a factor to express population growth and the industrial share of shrimp farming as a factor to show economic development, we can analyze the impact of those determinants on the EKC relationship.

Our initial results show strong evidence of the existence of an EKC relationship between mangrove loss and per capita income, correlating with many previous studies. This implies that mangrove forests in Thailand deteriorated during the 1970s and 1980s but would have recovered as the economy subsequently developed. The EKC turning point, which is the starting point of recovery, is at $5600 (1985 US$ level). However, the average per capita income of 23 provinces in Thailand, which is calculated from the collected data, is around $4000 (1985 US$ level) (and that number is based on 2004 data), which implies that the EKC turning point has not been reached yet in Thailand.

Our analysis of the impact of determinants on the EKC relationship shows that an increase in the population growth rate shifts EKC upward and accelerates mangrove deforestation. On the other hand, the results show that an increase in GPP growth rate shifts EKC downward and reduces mangrove deforestation. In other words, if the economic growth increases, then the mangrove forest is recovered. The results also show that shrimp farming significantly affects the extent of mangrove deforestation. More specifically, the development of extensive and semi-intensive shrimp farming techniques quickens mangrove deforestation, but intensive shrimp farming, which developed during the 1990s, reduces mangrove loss.

This paper is organized as follows. Section 2 presents the background of mangrove deforestation and the development of shrimp farming industry in Thailand. Section 3 provides empirical models, the hypothesis test, and estimation techniques. Section 4 explains the data used in this study. In section 5, the results are reported. The final section discusses the results.

2. Mangrove deforestation and shrimp farming

Mangrove, known as *manggi* in the Malay language, is a unique plant colony found in coastal streams and intertidal estuaries. Mangrove is mainly found in the subtropical and tropical zones north and south of the equatorial zone, approximately between 25 and 30° N. and S. in latitude (Walter, 1971). Most mangroves are woody trees or shrubs that belong to the

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[2] In the past studies on the EKC relationship to deforestation, many determinants of the EKC relationship have been found (Antle and Heidebrink, 1995; Barbier and Burgess, 2001; Bhattarai and Hammig, 2001; Cropper and Griffiths, 1994; Lopez and Galinato, 2005; Panayotou, 1993; Panayotou and Sungsuwan, 1994; and Shafik, 1994b), for example, population growth rate; population density; price of products (wood price, fuel price, and other substitutes price); structural factors (agricultural production, agricultural products export, technological change, and distance from markets); political factors (investment, accumulated debt, international trade, and land use); and institutional factors (economic system, political stability, political freedom, and security of ownership). Panayotou (1997) and Barbier and Burgess (2001) have particularly claimed that the industrial share is an important determinant of the EKC relationship.
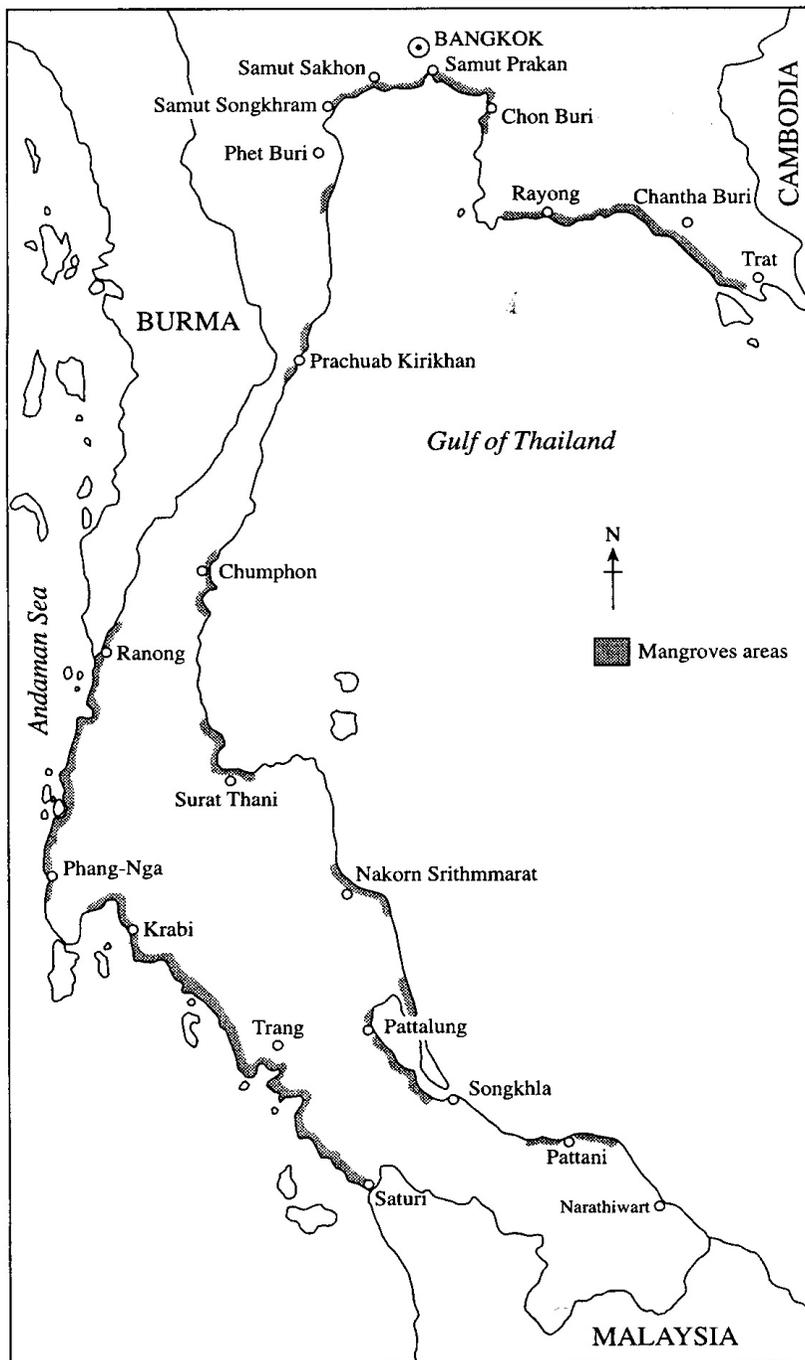
Figure 1. Habitats of mangrove in Thailand (23 provinces)

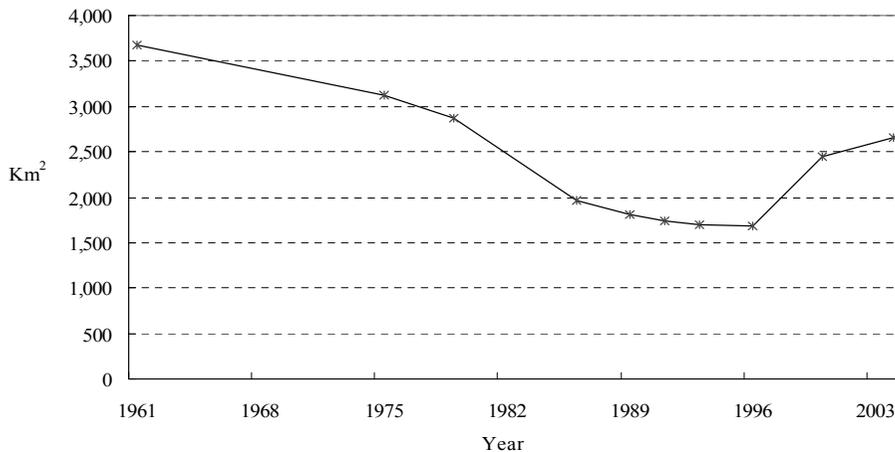*Source*: Aksornkoae and Tokrisna（2004）

Figure 2. Changes of mangrove area in Thailand (23 provinces), 1961 – 2004

Note: These are generated by using the data from the below source.

Source: Geo-Informatics, National Park, Wildlife and Plant Conservation.

Rhizophoraceae family, which is characterized by salt tolerance, thick leaves, and many aerial roots. Mangrove forms an important ecosystem between the land and the sea area that is indispensable plant and animal habitat. Moreover, mangrove plays an important role in stabilizing shorelines by protecting coastal streams and estuaries against tidal wave and soil erosion. Mangrove in Thailand inhabits 23 provinces (6 provinces on the coast of the Andaman Sea and 17 provinces on the coast of the Gulf of Thailand), approximately half of the total 2614 km coastline of Thailand (Aksornkoae and Tokrisna, 2004) (see Figure 1).

Figure 2 shows changes in the area covered by mangrove in Thailand (23 provinces) from 1961 to 2004. Mangrove in Thailand has been steadily deforested from 1961 to 1996 and has been reduced to about half of the original area, from 3679 km^2 in 1961 to 1685 km^2 in 1996. After 1996, however, mangrove forestation began to increase and reached 2658 km^2 in 2004, which is about 3/4 of the area covered by mangrove in 1961. In other words, in the 8 years between 1996 and 2004, mangrove forests recovered approximately half the loss experienced in previous years. In general, mangrove loss has been attributed to an increase in the demand for land as a result of population growth and economic development. The land converted from mangrove forest has been used for aquaculture (especially shrimp farming); agriculture; mining (tin); salt production; urbanization; construction of houses, factories, roads, and ports; and power plants. Illegal cutting for household timber and fuel has also impacted mangrove loss. (Aksornkoae and Tokrisna, 2004)

Figure 3 shows mangrove deforestation and its conversions to other land uses from 1991 to 1996 (the mangrove area in 1961 is set to 100%). The five bar graphs represent four regions in Thailand and the four-region total. These four regions are the Eastern region east of
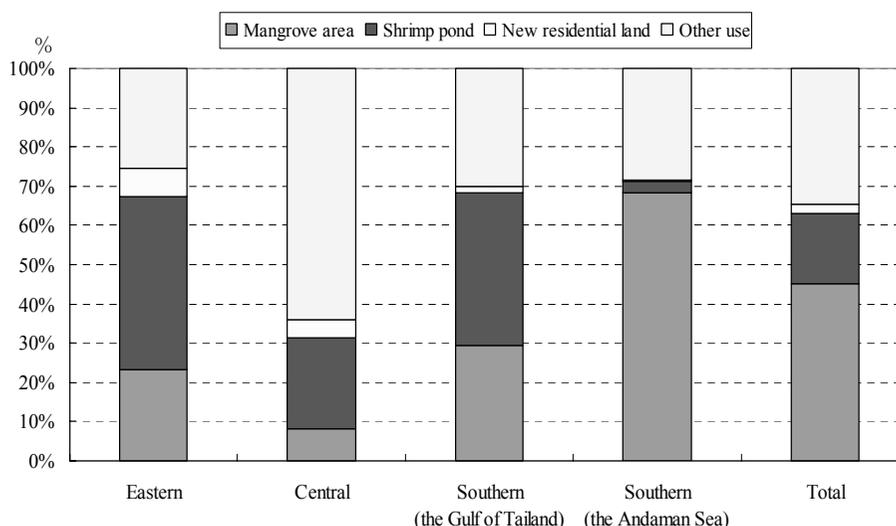
Figure 3. Mangrove deforestation and its conversions to the other land uses, 1991 – 1996

Note: The mangrove area in 1961 is set to 100%. These are generated by using the data from the below source.

Source: Geo-Informatics, National Park, Wildlife and Plant Conservation.

Bangkok (including 5 provinces); the Central region near Bangkok (including 6 provinces); the Southern region on the coast of the Gulf of Thailand (including 6 provinces); and the Southern region on the coast of the Andaman Sea (including 6 provinces). Looking overall at the four regions, 55% of the total mangrove area in 1961 had been deforested and about 18% (one third of destroyed mangrove area) converted into shrimp ponds by 1996. Another 2% of the mangrove area had been converted into new residential land and 35% converted for other uses.

The percentage of mangrove land converted into shrimp ponds is 44% in the Eastern region, 39% in the Southern region along the Gulf of Thailand, 23% in the Central region, and 2% in the Southern region along the Andaman Sea. Conversions into new residential land are very small— 7% in the Eastern region, 5% in the Central region, 2% in the Southern region along the Gulf of Thailand, and almost 0% in Southern region along the Andaman Sea. Conversions into other uses are most common in the Central region near Bangkok at around 64%, which is two times higher than the other three regions. A possible explanation might be that the demand for land for economic development is higher in the Bangkok area than in other regions.

The previous section demonstrated that deforestation in Thailand accounted for a loss of half of all mangrove forests during the 35 years from 1961 to 1996, and about one-third of the destroyed area has been converted into shrimp ponds. How has the shrimp culture industry in Thailand been developed during the same period? Figure 4 shows changes in the number of
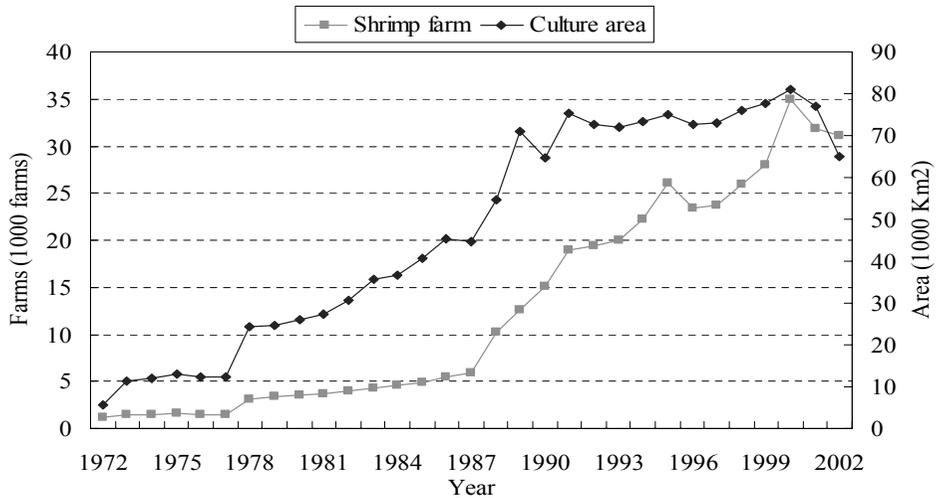
Figure 4. Changes of the number of shrimp farms and culture area in Thailand, 1972 - 2002

Note: These are generated by using the data from the below source.

Source: Statistics of Shrimp Culture, Department of Fisheries, Ministry of Agriculture and Cooperatives.

shrimp farms and culture areas in Thailand between 1972 and 2002. Both graphs clearly show a steady rise in the development of the shrimp culture industry in Thailand during this period.

It is helpful to examine the historical background of shrimp farming in Thailand.[3] In its early stages, shrimp production in Thailand was a by-product of salt production; wild shrimp strayed into the salt pans and were harvested. Subsequently, farmers stocked intentionally captured natural larvae in brackish ponds (a mixture of seawater and fresh water), then harvested them after the growth. This shrimp culture method is called "extensive shrimp farming[4]." Most brackish water ponds were usually converted from or were part of a salt pan. During this early period, the species raised were banana shrimp (*Peneaus merguiensis*) and school shrimp (*Metapenaeus sp*), which depended on natural larvae and fed on wild seaweed and plankton.

In the late 1960s, the number of shrimp farms started to increase gradually as rising shrimp prices made shrimp farming more profitable than salt production. Shrimp ponds were constructed on the coastline and the banks of canals by clearing mangrove trees and taking advantage of the natural tide system for water exchange. The success of artificial incubation for banana shrimp and black tiger shrimp (*Peneaus monodon*) in 1973 accelerated the increase

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[3] The history of shrimp culture in Thailand in this section is attributed to Aksornkoae and Tokrisna (2004).

[4] According to the census, extensive shrimp farming is defined as a culture method that uses only natural larvae and feeds in pond water that is derived from canals (Taya, 2003). The culture ponds used are relatively large, approximately 20-30 ha per pond. It takes 45-90 days for this method to raise shrimps, so the cost is low but the productivity is also low. In the semi-intensive shrimp farming method, farmers stock the larvae from the hatcheries (less than 24,000 fries per 1 rai (= 1600 m^2) of a pond), use artificial feed, and manage pond water by pumping from canals to improve the productivity. This culture system fits in between the extensive and intensive systems (a fuller explanation appears later).
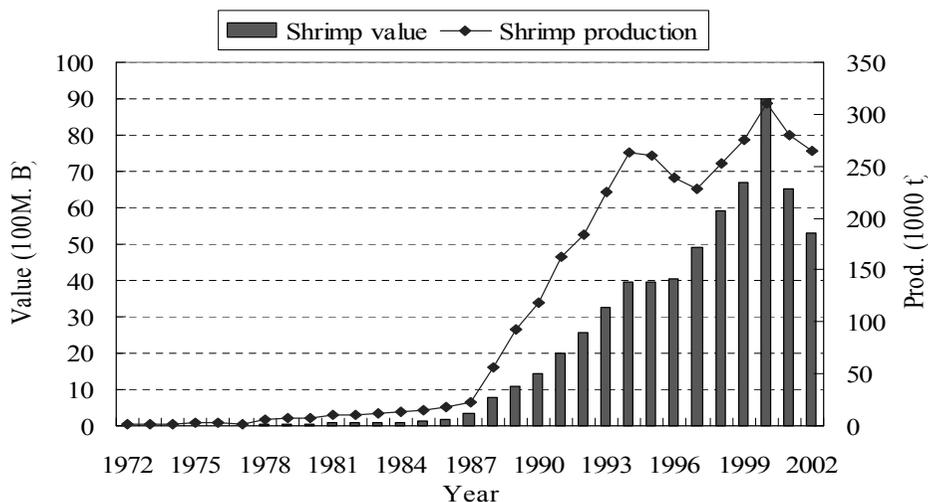
Figure 5. Changes of shrimp production and value in Thailand, 1972 - 2002

Note: These are generated by using the data from the below source.

Source: Statistics of Shrimp Culture, Department of Fisheries, Ministry of Agriculture and Cooperatives.

in shrimp farms. The number of shrimp farms gradually increased from 1972 to 1987, but after 1988 to 2000 they increased more rapidly due to the introduction of a new shrimp species, the black tiger shrimp, which had a higher profit rate because of its higher tolerance and better survival rate. In 1983, a multinational company from Taiwan started a joint venture with local investors, which used black tiger shrimp in an "intensive shrimp farming[5]" system. The development of this new technology caused a rapid increase in the number of shrimp farms after 1988.

In 1991, the Thai government enforced a new law (Cabinet Resolution) that prohibited the conversion of conserved and fertile mangrove areas into shrimp ponds, which slowed down the increase in shrimp farms temporarily during 1992 and 1993. Under this law, it became impossible to construct new shrimp ponds in the coastal area. However, investment in intensive shrimp farming continued to steadily increase since it did not require large shrimp ponds, which caused a rapid increase in the total number of shrimp farms from 1988 to 2000 (although there was a temporary decline because of the Asian economic crisis in 1997). This increase depended on the success of black tiger shrimp hatcheries, of course; at the same time,

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[5] This culture system uses a small pond, such as a rice field, in which shrimp is cultured by high larvae density and artificial mixed feed. To protect against disease infection, the farmers manage water quality by adding antibiotics and chemical products such as nutrients for 24 hours. Moreover, the farmers settle paddle wheel machines in shrimp ponds to maintain oxygen in the water, which is consumed during the decomposition of wastes from shrimp and artificial feeds. The culture ponds are small-sized, 0.5-1 ha per pond. According to the census, intensive shrimp farming is defined as a culture method that stocks more than 24,000 larvae per 1 rai, feeds 3-5 times per day, settles 1 paddle wheel per 1-2 rai of a pond, and takes 4-5 months for growth (Taya, 2003).

it was supported by the development of the shrimp feed industry, the technique of intensive shrimp farming, and the high shrimp price in the international market.

In more recent years (2001 and 2002), the number of shrimp farms decreased sharply. According to our field studies in Thailand, this was due to falling shrimp prices in the international market, possibly caused in part by an increase in shrimp production in other countries (such as Indonesia, Vietnam, and India). Indeed, even in the U.S., the largest importer of shrimp from Thailand, shrimp imports from Ecuador have increased gradually. Moreover, Thai shrimp farmers are confronted with the problems of infectious disease and lack of parental shrimps.

Another graph in Figure 4 shows changes in the shrimp culture area in Thailand from 1972 to 2002. The shrimp culture area, as well as the number of shrimp farms, showed an upward trend from 1972 to 1991. During the period between 1992 and 2000, however, the size of the shrimp culture area became stable. This was due to the Cabinet Resolution prohibiting the conversion of conserved and fertile mangrove areas into shrimp ponds; it also reflected the shift from extensive to intensive shrimp farming techniques. Intensive shrimp farming did not require the large shrimp ponds; therefore, this shift in the shrimp culture method gradually decreased mangrove deforestation.[6] Shrimp culture areas declined by 5% in 2001 and 16% in 2002, due to the shift in shrimp culture techniques.

Figure 5 shows changes in shrimp production (line graph) and value (bar graph) in Thailand from 1972 to 2002. Both graphs show an upward trend, similar to what the graphs in Figure 4 show for the number of shrimp farms and area. Production and value increased gradually until 1987, then experienced a rapid increase from 1988 to 1994, which is partially attributable to the impact of black tiger intensive shrimp farming beginning in 1983. From 1995 to 1997, shrimp production slowed down due to widespread shrimp infectious disease caused by the deterioration of water quality and nourishment. After 1998, the shrimp disease problems were solved and shrimp production increased again. The steady and rapid increase in shrimp value from 1988 to 2000 is due to the stability of the international market price of shrimp and the Japanese shrimp demand (Traesupap et al., 1999). Both shrimp production and value decreased in 2001 and 2002, which was caused by a decline in the international market price of shrimp.

3. Empirical model and hypothesis test

To analyze the EKC relationship between mangrove deforestation and income level, the empirical mode in this study uses the quadratic reduced form, which has been used for

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[6] In the1990s, the expansion of the culture area stabilized because of the shift to intensive shrimp farming and the development of a new culture system, called a "closed shrimp farming system." In this system, once the water is poured into the shrimp ponds, it almost needs no exchange. The farmers monitor the water condition and maintain a constant salt concentration. The water in the pond is imported from the sea by truck and it is carefully inspected before being poured into the pond. This system rapidly spread in the Central region near Bangkok starting around 1996, so that shrimp ponds have been constructed not only in the coastal areas but also in agricultural land in inland areas. In November 1998, however, the National Environment Board banned shrimp farming in freshwater areas (particularly in the Central region) out of concern about land chlorination and environmental degradation because too many agricultural lands were converted into ponds.

empirical EKC studies in general.[7]   This model includes per capita gross provincial production (GPP) and its square term to test the EKC hypothesis. Previous EKC studies for deforestation examined the reason why the EKC relationship exists and showed important determinants of EKC, such as population growth rate, population density, price of products, structural factors, political factors, and institutional factors. Hence this study adds the important determinants of mangrove deforestation --increasing population pressure (population growth rate and population density) and industrial structural change on the economy (industrial share)-- to the empirical model.

Population growth pressure indicates rising land demand, which is the main cause of deforestation, so it is always included in the empirical model. Population density data at the provincial level, however, is not available, so only the population growth rate is included as an explanatory variable in the model. Moreover, as a structural variable, the GPP share of the shrimp industry has a strong relationship to mangrove deforestation and is therefore included as one of explanatory variables in the model.

Industrial share affects the EKC relationship between mangrove deforestation and income level as follows. In the early stages of economic development, mangrove forests are intact. However, as the economy begins to change structurally, agriculture and fisheries shift to aquaculture and manufacturing. During this stage, both economic development and mangrove deforestation are underway. As the economy continues to develop and moves into the second structural change, those industries shift again to the service and informational and technological industries. In this stage, society can afford to pay attention to environmental degradation, and environmental protection laws are enforced and reforestation projects begun, which finally reduces mangrove loss.

The empirical model in this study is represented by the following equation:

$$MD_{it} = \alpha_i + \beta_1 Y_{it} + \beta_2 (Y_{it})^2 + \beta_3 \Delta Y_{it} + \beta_4 P_{it} + \beta_5 S_{it} + \beta_6 D_{it} + \varepsilon_{it,} \tag{1}$$

where, $i \; (= 1, …, n)$ is each province (23 provinces) and t is each year. Hence, MD_{it} indicates a mangrove deforestation index for i-th province in t-th year. In this study, as a mangrove deforestation index, both 'annual mangrove deforestation' and 'total mangrove deforestation' (used by Shafik and Bandyopadhyay, 1992) are utilized. The former is the yearly change in mangrove area and the latter is the change in mangrove area between the earliest date, 1975, and latest date.

Y_{it} is the Gross Provincial Product (GPP) per capita for i-th province in year t. $(Y_{it})^2$ is its square values; ΔY_{it} represents average GPP growth rate for i-th province in year t; P_{it} is Population Growth Rate for i-th province in year t; S_{it} is Shrimp Value Share for i-th province in year t; and D_{it} is dummy for the shock from the Asian Economic Crisis in 1997 and 98 (1 in the Crisis year, otherwise zero). Moreover, α_i is an intercept term that reflects technical innovation and cultural and social structure in i-th province; β's are coefficients for each

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[7] Although a log-quadratic model has been utilized in many empirical studies of the EKC relationship to deforestation, we could not use it because the mangrove deforestation index included some minus values.

variables; and ε's are disturbance terms.

As a pooled regression, the empirical model can be estimated using three different estimation techniques: the one point fixed model, the fixed effect model, and the random effect model. In the preliminary estimation, the no effect model was significantly rejected in favor of the fixed effect model using the F test, and the random effect model was significantly rejected in favor of the fixed effect model using the Hausman test. Therefore, in this estimation, the fixed effect model is employed.[8]

The fixed effect model is also referred to as the least squares dummy variable (LSDV) model, which has a cross section group-specific constant term in the estimation model. Since the pooled data used in this study was collected from 23 different provinces, there should be included some province-specific historical and structural differences. Therefore, the use of the fixed effect model is a reasonable choice here.

If the pooled data used in this model has different sizes according to each province size, the existence of a heteroscedasticity problem can be suspected. Hence, in the preliminary estimation, we also conducted the Wald test, after which the null hypothesis of homescedasticity was significantly rejected as predicted (there exists heteroscedasticity). To correct this problem, the weighted least square (WLS) approach is utilized in general. This technique transforms the variance of observation to give larger weight to observation with small variance. In this estimation, the two-stage feasible generalized least square (FGLS) technique is employed since only the cross section weight is considered.

On the other hand, since the pooled data used includes time-series data, the autocorrelation (AR) problem should be examined by using the Durbin-Watson (DW) statistic. If the null hypothesis (no autocorrelation) is rejected, the AR term should be included in the model to correct the autocorrelation. In that case, the iterated feasible generalized least square (iterated FGLS) approach is utilized for the estimation; however, care should be taken not to lose too many degrees of freedom in the estimation. While the effects of all combinations of the explanatory variables on mangrove deforestation are estimated by using the estimation model (1), at the same time, the EKC relationship between mangrove deforestation and income level is determined. To show the existence of the EKC hypothesis, the null hypothesis of both zero coefficients of β_1 and β_2 ($\beta_1 = \beta_2 = 0$) should be rejected and the alternative hypothesis ($\beta_1 > 0$ and $\beta_2 < 0$) accepted. If this alternative hypothesis is satisfied and demonstrates the evidence for the existence of EKC, it is useful to estimate an EKC turning point, which indicates the income level at which mangrove deforestation begins to decline. The EKC turning point can be calculated by dividing estimated coefficient, β_1 by $-2\beta_2$.

The sign for the estimated coefficient of the GPP growth rate, β_3 is unpredictable since it is situational. For example, if mangrove only plays an input role on the production process in Thailand, the increase in the GPP growth rate accelerates mangrove deforestation. However, if the GPP grows and the technology develops and mangrove is no longer necessary for inputs, then the increase on the GPP growth rate reduces mangrove loss. The sign for the estimated coefficient of population growth rate, β_4 is expected to be positive, because the rising pressure

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[8] See Chapter 13 in Greene (2003).

on population growth causes the increase in land demand, which quickens mangrove deforestation.

It is also difficult to predict the sign for the estimated coefficient of the industrial share on shrimp farming, β_5. In general, the development of the shrimp farming industry accelerates mangrove deforestation, but that is the case for extensive shrimp farming. As mentioned in section 2, shrimp farming has shifted from extensive to intensive shrimp farming techniques, which reduces mangrove deforestation. Therefore, the expected sign for the shrimp industrial share depends on the difference in shrimp value between the two culture techniques. Finally, the sign for the estimated coefficient of dummy variable, β_6 is expected as minus. An economic shock always decreases the production level in an economy, thereby working to reduce environmental degradation.

4. Data

This analysis uses pooled data on mangrove areas that combine cross sections on 23 provinces in Thailand and a time series of 10 years (1961, 75, 79, 86, 89, 91, 93, 96, 2000, and 2004). The data on mangrove areas, except for 1961 data, are very accurate since they are derived from a Landsat-5 (TM) satellite. Unfortunately, for 1961, data on 6 provinces are missing and data for the Eastern and Central areas are also extremely small values compared to 1975. Therefore, we suspect measurement errors or differences in methodology in 1961, and have removed the 1961 data from the analysis.

From the data on mangrove areas, we created 2 types of indexes, a "total mangrove deforestation" index and an "annual mangrove deforestation" index, which indicate the level of mangrove deforestation (the terms were first used by Shafik and Bandyopadhyay (1992))[9]. The former index is the change rate of mangrove areas between the base year of 1975 and other years (the unit is %), which is available for 22 provinces except Bangkok since its data in 1975 is zero. The latter index is the change of mangrove areas between years (the unit is square Km), which is available for all 23 provinces. Therefore, each index has 8 data points in the time series, so that the available observation numbers are 176 for the total mangrove deforestation index and 184 for the annual mangrove deforestation index.

The Gross Provincial Product (GPP) expresses the provincial level of Gross Domestic Product (GDP). Because the early studies of EKC used the 1985 US$ basis, we did the same, by converting the nominal GPP into the real GPP by using a GDP deflator with the 1985 US$ basis (= 100). This allows us to compare our results with the early studies and possibly avoid some autocorrelation problems in the time series data. In our analysis, the GPP per

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[9] The 'total mangrove deforestation' index is calculated by dividing the difference between the mangrove area in the base year of 1975 ($M_{i,75}$) and the one in year t ($M_{i,t}$) by the one in 1975 ($M_{i,75}$); and multiplying 100;

$$ML_{i,t} = \frac{(M_{i,75} - M_{i,t}) \times 100}{M_{i,75}}, \quad (i = 1, 2, \ldots, 22 \text{ provinces except Bangkok}).$$

The 'annual mangrove deforestation' index is simply calculated by extracting the mangrove area in year t-1 ($M_{i,t-1}$) from the one in year t ($M_{i,t}$);

$$ML_{i,t} = M_{i,t} - M_{i,t-1}, \quad (i = 1, 2, \ldots, 23 \text{ provinces}).$$

capita is used, so each GPP is divided by the population in each province. Moreover, the GPP growth rate is not the per capita level but the per province level.

As mentioned in Section 2, the data for Thailand's total number of shrimp farms, culture area, shrimp production, and shrimp value are available from 1972 to 2002. The data on the provincial level, however, are limited from 1976 to 2002. Since the provincial data for mangrove area, GPP, and population are available from 1975 to 2004, we utilized the data for shrimp production in 1976 and 2002 as proxies for 1975 and 2004, respectively. The industrial share of shrimp farming to total GPP is calculated by dividing the shrimp production in each province by the GPP in each province (1985 US $ level). There are many zero level of shrimp production and value in the early years of the data; in those cases, however, the zeros were kept intact and used for the estimation.

Finally, the sources of the data are listed in Table A1 in the Appendix. The statistics for all data are also shown in Table A2 in the Appendix. We can see there is a wide variance in the data from the table. The size of the data indeed depends on the situation in each province. The average of GPP data is 49880 Thailand Baht, which is converted into US$1833 (1985 US $ level).

5. Empirical Results

Table 1 shows the estimation results of the regression equation (1) in the case of model□, Table 1 shows the estimation results of the regression equation (1) in the case of model I, which uses total shrimp industrial share. The left-hand column presents the estimation results using the total mangrove deforestation index as an explained variable (Case 1); the right-hand column presents results based on the annual mangrove deforestation index as an explained variable (Case 2). In the preliminary estimation for case 1, Durbin-Watson (DW) statistics shows 1.350 ($< d_l = 1.57$), which indicates the existence of a positive autocorrelation problem. We added the AR (1) term in the fixed effect model to correct the problem; however, we could not estimate the model because of the singular variance-covariance matrix. Therefore, we used the no effect model with the AR(1) and AR(2) terms by using iterated feasible weighted least square (FGLS) in model I.

In case 1, the number of cross sections in the data is 22, because the Bangkok province is excluded as mentioned in previous section. The time series data includes 8 years, from 1979 to 2004, so that the number of total observations is 176, but the degrees of freedom reduced to 132 by correcting autocorrelation. The Adjusted R^2 is 0.916, which indicates the high explanatory power of the model. The F-value is also very high at 179.9. After correcting autocorrelation, the DW statistics are 1.887 ($> d_u = 1.78$), in which the null hypothesis of no autocorrelation ($\rho = 0$) was not rejected.

In case 1, the estimated coefficient for the GPP per capita has the expected positive sign ($\beta_1 > 0$) and is statistically significant at the 1% confidence level. The estimated coefficient for the GPP per capita squared has the expected negative sign ($\beta_2 < 0$) and is statistically significant at the 5% confidence level. These results strongly suggest the existence of the

Table 1. Estimates for Model I

(Explanatory variables)	Case 1 (Total deforestation index)	Case 2 (Annual deforestation index)
Constants	−20.65 (23.75)	−6.502 (5.062)
GPP per capita	0.481 (0.179) ***	0.172 (0.083) **
GPP per capita squared	−0.0010 (0.0005) **	−0.00049 (0.00021) **
GPP growth rate	−0.069 (0.036) *	−0.087 (0.055)
Population growth rate	0.304 (0.189)	1.535 (0.411) ***
Industry share of shrimp farming	0.040 (0.189)	−0.435 (0.460)
Dummy for Asian Economic Crisis	−9.050 (2.249) ***	−29.93 (7.699) ***
Adjusted R^2	0.916	0.410
DW	1.887	2.130
F-value（P-value）	179.9 (0.000)	5.538 (0.000)
The number of cross-section	22	23
The number of time series	8 (1979-2004)	8 (1979-2004)
Observations （with AR）	176 (132)	184
EKC turning point (1985US＄)	$8451	$6505
Estimation model	No effect + AR + WLS	Fixed effect + WLS

Note1: Standard errors are in parentheses.

Note2: *, **, and *** are statistically significant at 10, 5, and 1 % significance level.

Note3: EKC turning points are calculated by using international exchange rate (US$1 = 27.21THB).

EKC hypothesis. The estimated coefficient for the GPP growth rate shows negative sign and is statistically significant at the 10% confidence level, which means that the increase of GPP growth reduces mangrove deforestation.   Moreover, the estimated coefficient for the population growth rate has the expected positive sign, but it is not satisfied with the 10% level of significance (it is 11% of significance, however). This weakly suggests that the rising of the population growth rate accelerates mangrove deforestation.

On the other hand, in the preliminary estimation of case 2, using the DW test, the null hypothesis is not rejected (DW statistics are 2.130 < 4-d_u = 2.22), making it unnecessary to correct autocorrelation. Hence, in case 2 the fixed effect model is estimated by two-step FGLS. The number of cross sections in the data is 23, all of which are provinces possessing mangrove. The number of observations is 184, and all were gathered from a time series of 8 years, from 1979 to 2004. However, the adjusted R^2 is 0.410, which indicates a lower

Table 2. Estimates for Model II

(Explanatory variables)	Case 1 (Total deforestation index)	Case 2 (Annual deforestation index)
Constants	−101.4	−4.099
	(77.463)	(4.370)
GPP per capita	0.932	0.105
	(0.163)***	(0.061)*
GPP per capita squared	−0.0022	−0.0003
	(0.0005)***	(0.0002)**
GPP growth rate	−0.099	−0.119
	(0.045)**	(0.059)**
Population growth rate	−0.134	1.573
	(0.102)	(0.388)***
Industry share of		
Extensive and semi-intensive	−3.239	8.724
shrimp farming	(1.755)*	(2.249)***
Intensive shrimp farming	0.363	−0.795
	(0.070)***	(0.429)*
Dummy	−9.576	−28.77
for Asian Economic Crisis	(1.680)***	(7.200)***
Adjusted R^2	0.930	0.439
DW	2.053	2.096
F-value（P-value）	60.58 (0.000)	5.325 (0.000)
The number of cross-section	22	23
The number of time series	7 (1986-2004)	7 (1986-2004)
Observations （with AR）	154(132)	161
EKC turning point (1985US＄)	$7690	$5615
Estimation model	Fixed effect + AR + WLS	Fixed effect + WLS

Note1: Standard errors are in parentheses.

Note2: *, **, and *** are statistically significant at 10, 5, and 1 % significance level.

Note3: EKC turning points are calculated by using international exchange rate (US$1 = 27.21THB).

explanatory power of the model than in case 1, and the *F*-value reduces from 179.9 to 5.538.

In the estimation results in case 2, the estimated coefficients for the GPP per capita and the GPP per capita squared have the expected signs ($\beta_1 > 0$ and $\beta_2 < 0$) and are both statistically significant at the 5% confidence level. These results, like the case 1 results, strongly suggest the existence of the EKC hypothesis. The estimated coefficient for the GPP growth rate also shows a negative sign but is not statistically significant. Hence, in case 2 we cannot reach a conclusion about the relationship between GPP growth rate and the EKC. The estimated coefficient for the population growth rate has the expected positive sign, as in case 1, and is statistically significant at the 1% confidence level. This strongly suggests that the increase in

the population growth rate accelerates mangrove deforestation.

The estimated coefficients for the industrial share of shrimp farming have a positive sign in case 1 and a negative sign in case 2, neither of which are statistically significant. These signs depend on how many shares based on data from extensive or intensive shrimp farming, as mentioned in section 3. The industrial share from extensive farming accelerates mangrove deforestation but the industrial share from intensive farming reduces mangrove destruction. Since the industrial share results here are derived from a combination of these two farming methods, we cannot conclude anything statistically. Therefore, we analyze model II by dividing all industrial shares into categories of extensive or intensive shrimp farms.

Table 2 presents the estimation results for model II, which includes two parts of the industrial share of the extensive and intensive shrimp farms (the semi-intensive shrimp farming is included in the share of the extensive shrimp farm since the size of their shrimp ponds is very similar). In the same way as model I, the total mangrove deforestation index is used as an explained variable in case 1 and the annual mangrove deforestation index is employed as an explained variable in case 2. Since the data for the extensive and intensive shrimp farming are only available from 1987 to 2002, we used the data for 1987 and 2002 as proxies for 1986 and 2004, respectively. Therefore, the number of observations is 154 in case 1 and 161 in case 2.

In case 1 of the model II, the preliminary estimation shows DW statistics of 1.368 ($< d_l =$ 1.57), which indicates positive autocorrelation, so we corrected the problem by adding an AR(1) term in the model (after correction, DW statistics are 2.053). Hence, in case 1 the fixed effect model is estimated by using iterated FGLS with an AR(1) term. The estimation results in case 1 show that the adjusted R^2 is 0.930, which indicates a high explanatory power of the model; the F-value is also very high at 60.58. The estimated coefficient for the GPP per capita and the GPP squared both have the expected signs and both are statistically significant at the 1% confidence level. Hence, the results in case 1 also suggest the existence of the EKC hypothesis in model II. The estimated coefficient for the GPP growth rate shows a negative sign like model I and is statistically significant at the 5% confidence level. However, the estimated coefficient for the population growth rate has a negative sign, which is the inverse sign in model I and is not statistically significant.

In case 2, there is no autocorrelation problem in the preliminary estimation; therefore, we estimated the fixed effect model by using the two-step FGLS. The time series data includes 7 years between 1986 and 2004 and the number of observations is 161. The adjusted R^2 is 0.439, which indicates a lower explanatory power of the model than in case 1 and the F-value is also smaller than in case 1. The estimated coefficient for the GPP per capita and the GPP squared both have the expected signs as well as in case 2 in model I and are statistically significant at the 5 and 10% confidence level, respectively. Hence, the EKC hypothesis is satisfied in case 2. The estimated coefficient for the GPP growth rate shows a negative sign and is statistically significant at the 10% confidence level (it is not statistically significant in case 2 in model II). The estimated coefficient for the population growth rate has the expected positive sign and is statistically significant at the 1% confidence level.

The estimated coefficient for the industrial shares in case 1 has the opposite sign from the one in case 2, but they are both statistically significant. In case 1, the estimated coefficients for the industrial share of both the extensive and semi-intensive shrimp farming and the intensive shrimp farming do not have the expected signs, but they are statistically significant at the 10% and 1% confidence level, respectively. In case 2, however, both industrial shares have the expected signs; the former is statistically significant at the 1% confidence level and the latter at the 10% confidence level. Therefore, the results strongly suggest that extensive and semi-intensive shrimp farming accelerate mangrove deforestation and intensive shrimp farming reduces mangrove destruction in case 2.

6. Discussion

First of all, we examined the existence of the EKC hypothesis and an EKC turning point based on the estimation results. In both models I and II, the estimated coefficients for the GPP per capita and the GPP per capita squared were satisfied with the expected signs. Also, they were statistically significant at the 1% or 5% confidence level except the GPP per capita term in model II, which were significant at the 10% level. Therefore, we can conclude that our results provide strong evidence of the existence of an EKC relationship between mangrove deforestation and income level in Thailand. That is, mangrove deforestation in Thailand increases as the income level rises, but the forests begin to recover once income reaches a threshold level.

From the estimated coefficients of β_1 and β_2 in model I, the EKC turning points are calculated as $8451 in case 1 and $6505 in case 2 (1985 US$ base). In model II, the EKC turning points are computed as $7690 in case 1 and $5615 in case 2 (1985 US$ base). The EKC turning point in case 1 (the total mangrove deforestation index is used) in both models I and II are very similar to the results of a study by Lopez and Galinato (2005), in which turning points were calculated between $7000 and $8000 in the case of deforestation in Brazil, Malaysia, and the Philippines.

On the other hand, the EKC turning points in case 2 (the annual mangrove deforestation index is used) in both models I and II are very close to those in the study by Barbier and Burgess (2001), which were computed as $6182 in the case of deforestation in Asia. The fact that our estimated EKC turning points are very close to previous estimates strengthens the evidence of the existence of the EKC hypothesis. There is a difference of about $2000 in the EKC turning points of the total mangrove deforestation index and the annual mangrove deforestation index. This is because the former index recovers more slowly than the latter index (the shape of the EKC in the former index is flatter than the latter index).

Although the minimum EKC turning point calculated was $5615 (in case 2 in model II), it is impossible for mangrove loss to recover if the turning point is far from the present GPP per capita in Thailand. If we calculate the GPP per capita in 23 provinces in Thailand from the collected data, it is about $4000 (1985 US$ base) even in 2004. Hence, the EKC turning point that is the starting point for mangrove loss recovery has not yet been reached in Thailand.

Based on the collected data, however, the annual mangrove deforestation indexes show minus values in 22 provinces out of 23 provinces in 2000, which indicates recovery of mangrove loss in Thailand has already begun.

Next, we examined the effects of the shrimp farming industry on mangrove deforestation in Thailand. When the total industrial share of shrimp farming as a whole was used in model I, we did not get any useful results at all. However, when we included two divided industrial shares by shrimp culture technology in model II, we did get useful results. In model II, the estimation results in case 2 are stable and robust compared to the ones in case 1, because the former results did not change much between models I and II but the latter results did. Therefore the estimation results in case 2 are more reliable than the ones in case 1. This might be the case because the autocorrelation was corrected at the expense of losing many degrees of freedom in case 1, which was not necessary in case 2.

Hence, we examined the relationship between shrimp farming and mangrove deforestation based on case 2 only. From the estimation results, it was confirmed that the development of extensive and semi-intensive shrimp farming techniques accelerated mangrove deforestation (shifted EKC upward) and the development of intensive shrimp farming reduced mangrove loss. As stated in section 2, many mangrove forests were cut down to create ponds for shrimp farming in the early stages of extensive shrimp farming; however, it was no longer necessary to clear forest in the 1980s, when intensive shrimp farming started to develop. The results of this study provide evidence that the development of technology in shrimp culture contributes to the reduction of mangrove deforestation.

In addition, the results of the factor analysis for mangrove deforestation clearly demonstrate that the rise of the population growth rate accelerated mangrove deforestation by shifting the EKC upward. This result supports the viewpoint that the fundamental cause of mangrove deforestation is increased demand for land due to population growth. It is also clear that as the GPP growth rate increases, mangrove loss is reduced and the EKC shifts downward. The faster the GPP growth, the higher the mangrove loss recovery.

Also worthy of mention are the estimation results of the dummy variable used for expressing the effect of the Asian Economic Crisis in 1997 and 1998 on mangrove deforestation. The estimated coefficients for the dummy variable have the expected negative signs and are statistically significant at the 1% confidence level in all cases in both models. These results strongly suggest that the Asian Economic Crisis slowed down the economy in Thailand, which reduced mangrove loss. In the same way that Moomaw and Unruh (1997) demonstrated the relationship between the EKC hypothesis and the Oil Crisis in 1979, these results demonstrate that the Asian Economic Crisis in the 1990s had the effect of stabilizing mangrove deforestation.

While the existence of an EKC relationship between mangrove deforestation and income level is indicated, some caution should be used in interpreting the empirical results. It is impossible to generalize the EKC hypothesis from these results, as pointed out by Arrow et al. (1995): "Economic growth is not a panacea for environmental quality." In this study, we examined mangrove deforestation in Thailand, where economic development had been far

ahead of other developing Asian countries. Hence, the EKC hypothesis confirmed in this study does not necessarily fit in Indonesia and Vietnam, which are facing the same problem of mangrove deforestation. Moreover, although mangrove trees recover relatively easily, it may take hundreds of years for primeval forests to recover, and it may be impossible for fishery resources to recover.

This study remains incomplete due mainly to lack of data. We need annual data on mangrove area and pre-1975 data for more precise analysis; we also need data on population density for each province, which is always used in EKC studies as the causing factor of deforestation. Moreover, to examine the causing factor of the EKC, we should not only include industrial share as an explanatory variable in the model, but also international trade values, political factors (policies for land use and investment for reforestation projects), and institutional factors (ownership and corruption). Indeed, the Thai government enforced a new law (Cabinet Resolution) that prohibited the conversion of mangrove areas into shrimp ponds in 1991 and 1998 and began the major project of reforestation. Another factor that deserves attention is the tendency of companies in Thailand to bribe government officials to break environmental protection laws. These analyses are left for future research.

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Appendix

Table A2. List of data sources

Data	Source
Mangrove area（23 provinces）	Geo-Informatics, National Park, Wildlife and Plant Conservation
GPP（23 provinces）	Office of the National Economic and Social Development Board, Office of the Prime Minister
GDP deflator	Economic and Financial Statistics, Bank of Thailand
International exchange rate	Bank of Thailand
Population（23 provinces）	Registration Division, Local Administration Department, Ministry of Interior
Shrimp value（23 provinces）	Statistics of Shrimp Culture, Department of Fisheries, Ministry of Agriculture and Cooperatives

Table A2. Summary statistics for data

Explanatory variables	Annual deforestation index	Total deforestation index	GPP per capita	GPP per capita squared	GPP growth rate	Population growth rate	Industrial share of shrimp farming
Mean	2.548	35.79	49.88	5182	18.18	6.794	4.861
Median	1.189	37.83	30.74	944.9	16.13	5.095	1.919
Maximum	142.7	100.0	335.1	112308	147.0	34.80	49.72
Minimum	-181.3	-411.6	8.150	66.40	-42.87	-4.769	0
Standard deviation	33.11	61.46	52.05	12943	24.56	6.576	7.793
Observations number	184	176	184	184	184	184	184
Cross-section number	23	22	23	23	23	23	23