The Effects of Forestland Ownership Conversion on Greenhouse Gas Emissions:

The Case of South Korea

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ABSTRACT. *This research analyzed the effects of forestland conversion from private to public ownership on greenhouse gas emissions by quantifying the relationship between forestland ownership conversion and deforestation, and then examining the effects of the change in deforestation on greenhouse gas emissions in South Korea. Ex ante simulations forecast greenhouse gas emissions resulting from deforestation rates under the current level of national forestland and three scenarios of increased percentages of national forestland. The findings suggest that increasing the percentage of national forestland would mitigate the increase in the deforestation rate, which in turn would moderate the increase in greenhouse gas emissions.* (JEL Q15, Q23, Q24, Q54)

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I. INTRODUCTION

South Korea has recently set a voluntary target for reducing emissions and is pushing a "low-carbon, green-growth" policy (United Press International 2009). The low-carbon, green-growth policy is intended to promote green industries as new growth engines that also reduce greenhouse gas emissions (Hunton & Williams LLP 2010). The "five-year green growth plan" under the policy announced in July 2009 aims to spend $87 billion on a variety of projects to reduce emissions and develop technologies in various areas (The Associated Press 2009). Consequently, changes in land development patterns seem inevitable in the near future as the plan requires green growth that increases the efficiency of land use while simultaneiously reducing pollution from land use (Mendelsohn 2009).

A major anticipated change during the span of the "five-year green growth plan" is the implementation of low carbon urban environments through sustainable land development. The government is beginning to advocate balanced land management througout the country, focusing particular attention on the conservation of forestland, which accounts for 65% (or 6.46 million hectares) of the country's land area (Korean Forest Service 2009). For example, the Korean Forest Service has established a long-term plan to purchase 30,000 hactares of private forestland during the 1996-2050 period, after which approximately 40% of available forestland in the country will be nationally owned. The plan has been formed specifically to decrease the rate of deforestation by increasing the portion of national forestland in the country for the expansion of carbon sinks (Korean Forest Service 2008).

A number of studies have shown that forest conservation initiatives, such as the Korean Forest Service's long-term plan, can play a critical role in reducing greenhouse gas emissions (e.g., Brand and Kuppalli 2005; Hertel et al. 2006; Moura-Costa and Stuart 1998; Stavins and Richards 2005). Common findings in previous studies include (1) conserved forest reduces greenhouse gas emissions by avoiding emissions through prevention or reduction of deforestation and (2) forest conservation provides a cost effective way to curb greenhouse gas emissions. While these studies have enhanced our knowledge of the relationship between forest conservation and greenhouse gas emissions, because they focused on the relationship utilizing macro-level data (e.g., national- and/or global-level data), they inherently did not evaluate how changes in forestland ownership within a country, or within regions within a country, affect greenhouse gas emissions.

This study uses micro-level data at the county level to analyze the extent to which greenhouse gas emissions are affected by the Korean Forest Service's long-term plan to purchase private forestland for conservation purposes, focusing on how forestland ownership conversion affects the change in deforestation and how the resulting change in deforestation affects greenhouse gas emissions. A two-stage, instrumental-variable regression model is used to quantify the relationship. In the first-stage regression, the current-period deforestation rate is the dependent variable, and forestland ownership and the lagged rate of deforestation serve as unique instrumental variables (referred to as the "deforestation model"). The second-stage regression includes change in greenhouse gas emissions as the dependent variable and the predicted deforestation rate from the first stage as an explanatory variable (referred to as the "greenhouse gas emission model").

The use of micro-level data presents a challenge related to the spatial structures of deforestation and greenhouse gas emissions. Deforestation and emission levels of neighboring counties would likely exhibit high error dependence in the deforestation and greenhouse gas emission models as they may be co-determined through neighborhood spillover effects (Ma et al. 2009; Mooney et al. 2007; Reis and Guzman 1992). Thus, there is a need to control for spatial correlations in the errors due to potential spatial dependencies in each model. Consequently, general spatial processes are assumed for the deforestation model in the first stage and the greenhouse gas emission model in the second stage.

Once estimates are acquired from the two models, the impact of the long-term planned acquisiton of private forestland on greenhouse gas emissions is evaluated by *ex ante* simulations of the effect of ownership changes on deforestation and the effect of deforestion on greenhouse gas emissions. The *ex ante* simulations forecast greenhouse gas emissions that result from deforestation under both the current level of nationally owned forestland and the 1996-2050 plan to purchase private forestland under the *ceteris paribus* assumption. The effects of the long-term plan on deforestation and greenhouse gas emissions are quantified by comparing the simulation results with and without the long-term plan.

Forecasting the change in greenhouse gas emissions due to anticipated changes in forestland conservation is important for making informed policy and planning decisions to help South Korea achieve its voluntary target for reducing emissions. Generating greenhouse gas emission estimates under different forestland ownership scenarios will provide an additional tool to help policymakers anticipate the impact of forestland conservation on greenhouse gas emissions. More specifically, the potential effectiveness of the long-term plan in supporting the country's target can be evaluated based on different forestland ownership scenarios and the extent to which greenhouse gases are mitigated by restraining deforestation.

II. EMPIRICAL MODEL

Specification of Deforestion and Greenhouse Gas Emission Models

We hypothesize that the change in greenhouse gas emissions during a given time period and the corresponding deforestation during the same period are explained by the framework of the following two-step regression method:

$$\begin{pmatrix} y_i^g \\ y_i^d \end{pmatrix} = \begin{pmatrix} \gamma_g^d \hat{y}_i^d + \delta_g' X_i^g \\ \delta_d' X_i^d \end{pmatrix} + \begin{pmatrix} e_i^g \\ e_i^d \end{pmatrix}, \qquad [1]$$

where y_i^g is the percentage change in greenhouse gas emissions between 2000 and 2005 in county i, y_i^d is the rate of deforestation between 2000 and 2005 for i, $\hat{y}_i^d$ is the estimated rate of deforestation during the same period for i, and e is a random disturbance term for i. The rate of deforestation is hypothesized to be endogenous. Exogenous variables hypothesized to explain the percentage change in greenhouse gas emissions in county i are contained in X_i^g, including lagged socioeconomic status (e.g., population density, per capita GDP), environmental features (e.g., elevation, precipitation, temperature), distance measures (e.g., distance to a major city, distance to seaside), and predetermined (lagged) percentage change in greenhouse gas emissions. Exogenous variables explaining the rate of deforestation in county i are in X_i^d, including lagged socioeconomic status, environmental features, distance measures, predetermined (lagged) rate of deforestation, and nationally owned forestland as a percentage of total forestland (hereafater referred as "percentage of national forestland"). The lagged rate of deforestation and percentage of national forestland are unique instruments for the deforestation model. γ_g^d is a scalar parameter and δ_g, and δ_d are conformable parameter vectors.

Determining Hypothetical Percentage of National Forestland

Hypothetical percentages of nationally owned forestland were determined loosely based on the Korean Forest Service's long-term plan with a given budget of \$7.5 billion to purchase private forestland for the expansion of carbon sinks.[1] Specifically, three purchase scenarios were established under the *ceteris paribus* assumption, given the budget: (1) purchase forestland in descending order of greenhouse gas emissions in each county, (2) purchase forestland in ascending order of forestland price in each county, and (3) purchase the same amount of forestland in each county with some exceptions (see details below). Scenario (1) was established to reduce greenhouse gas emissions by giving priority to the counties with higher emission rates. Scenario (2) was intended to maximize the amount of purchased land. Scenario (3) was established to scale coverage of acquired forestland across the country so the percentage of nationally owned forestland in each county does not exceed 40% of total county forestland. The 40% county target was chosen because it mirrors the national target of the Korean Forest Service's long-term plan. Figures 1, 2, and 3 highlight counties with forestland purchases under Scenarios (1), (2), and (3), respectively.

The purchased area for each county under the scenario (3) was determined using a simple optimization procedure: $\underset{A_i}{Max}\sum_{i=1}^{n} A_i \times P_i \leq M$, subject to $\frac{A_i + NF_i}{F_i} \leq 0.4$ and $A_i \leq PF_i$, where n is number of counties, M is the Korean Forest Service's \$7.5 billion budget, A_i is the area of private forestland purchased, P_i is the average per unit price of private forestland, NF_i is the area of nationally owned forestland, F_i is the area of all forestland, and PF_i is the available area of privately owned forestland in county i.

The optimization procedure ensures that an equal amount of forestland is purchased (i.e., $A_i = A_j,\ i \neq j$) except (i) in counties where national forestland is currently equal to or greater than 40% of total forestland, $\frac{NF_i}{F_i} \geq 0.4$, (ii) in counties where national forestland is currently less than 40% of the total forestland and the sum of national forestland and private forestland is equal to or greater than 40% of the total forestland after the purchase of the equal amount of forestland, $\frac{NF_i}{F_i} < 0.4$ and $\frac{A_i + NF_i}{F_i} \geq 0.4$, or (iii) in the counties where national forestland is currently less than 40% of the total forestland and the sum of national forestland and private forestland is less than 40% of the total forestland after the purchase of the equal amount of forestland, $\frac{NF_i}{F_i} < 0.4$ and $\frac{A_i + NF_i}{F_i} < 0.4$. To accommodate these exceptional cases, no private forestland was assumed to be purchased for the case (i), the area of private forestland that is equivalent to the 40% of entire forestlands minus the area of national forestland was assumed to be purchased for the case (ii), and all available private forestland was assumed to be purchased for the case (iii).

General Moment Estimation of The SARAR (1,1) and the Forecasting of Deforestation and Greenhouse Gas Emissions

A spatial process model where an endogenous variable is specified to depend on spatial interactions between cross-sectional units plus a disturbance term was modelled as a weighted average of nearby cross-sectional units (Cho, Lambert, and Roberts 2010). A general spatial model (Anselin 1988 p 64-65 and 182-183; Kelejian and Prucha 2010) that contains a spatially lagged endogenous variable and a spatially autoregressive disturbance in addition to exogenous variables (or a spatial autoregressive model with autoregressive (AR) disturbance of order (1,1) (SARAR)) was used to estimate the deforestation model in the first stage and the greenhouse gas emission model in the second stage as follows:

$$y = \rho W_1 y + X\beta + e, \ \ e = \lambda W_2 e + u, \tag{2}$$

where W_1 and W_2 are (possibly identical) nonstochastic, positive definite, exogenous matrices defining interrelationships between spatial units and u is a random error term. The reduced–form version is:

$$y = A^{-1}X\beta + A^{-1}B^{-1}u; \ \ A = (I - \rho W_1), \ \ B = (I - \lambda W_2), \tag{3}$$

where ρ = a spatial lag regressive term and λ = a spatial error autoregressive term. The spatial process model is estimated using the generalized method of moments (GMM) procedure that extends Kelejian and Prucha's (2004) system estimator to an estimator robust to the unspecified forms of heteroskedasticity recently suggested by Arraiz et al. (2010).

Kelejian and Prucha's (2007) procedure for the SARAR (1,1) is applied to generate forecasts for the rate of deforestation and the percentage change in greenhouse gas emissions. The forecasts facilitate *ex ante* comparisons between the predicted greenhouse gas emissions based on the observed percentage of national forestland as the baseline scenario and the predicted greenhouse gas emissions based on the three scenarios of hypothetical percentages of national forestland mentioned in the subsection above. The predictor is expressed as the reduced form Equation [4], and the structural Equation [5]:

$$\hat{y} = \hat{A}^{-1}X\hat{\beta} \tag{4}$$

$$\hat{y} = \hat{\rho} W_1 y + X\hat{\beta} \, . \quad [5]$$

Specification of Matrix Defining Interrelationships between Spatial Units

In the general spatial model, the selection of an appropriate exogenous matrix defining interrelationships between spatial units **W** (hereafter referred to as "spatial weight matrix") remains a challenge. In general, there is no consensus as to which weights are most appropriate for any econometric study (Anselin 1988). Four types of spatial weight matrices **W** (i.e., the Queen contiguity, *k*-nearest neighbor, inverse distance, and hybrid spatial weight matrices) were considered to test various neighborhood structures.

Different orders of Queen contiguity weight matrices **W** based on county boundaries (e.g., first-, second-, and third-order Queen contiguity weight matrix) were constructed.[2] The first-order Queen contiguity weight matrix was structured so that if the *i*th and *j*th counties share a common geographic border or vertex, the elements of the spatial weight matrix W_{ij} have a value of 1, and 0 otherwise. The diagonal elements of **W** have a value of 0. The second-order Queen contiguity weight matrix was structured so that if the *i*th and *j*th counties share a common geographic border or vertex or if the *i*th and *j*th counties have a common neighbor with which they directly share a border or a vertex, the elements of the spatial weight matrix $\mathbf{W}_{ij}$ have a value of 1, and 0 otherwise. The diagonal elements of **W** have a value of 0. The third-order Queen contiguity weight matrix was constructed following the same logic.

The *k*-nearest neighbor (KNN) weight matrix was constructed in such a way that the number (*k*) of nearest neighbor counties was identified based on the Euclidean distances between any two possible centroids of counties. Given the identified KNN, **W** was structured in such a way that if the counties i and j were identified as neighbors, the elements of the spatial weight matrix $\mathbf{W}_{ij}$ took the value of 1, and 0 otherwise. The diagonal elements took the value of 0. A series of 2-4 neighbors (i.e., k = 2, 3, and 4) was used to construct the KNN weight matrices.

The inverse distance weight matrix was constructed in such a way that the elements of the spatial weight matrix $\mathbf{W}_{ij}$ take the inverse of Euclidean distances between any two possible centroids of counties (i and j), and the diagonal elements of $\mathbf{W}$ have a value of 0. Two types of hybrid spatial weight matrices were constructed by element-wise multiplications (1) between the order of Queen contiguity weight matrix and the inverse distance weight matrix and (2) between the k-nearest neighbor weight matrix and the inverse distance weight matrix. The hybrid spatial weight matrices allow for distance-decay effects among the first-, second-, and third-order Queen contiguity weight matrices and the KNN (k = 2, 3, and 4) weight matrix. All spatial weight matrices described above were row standardized so that each row sums to one, which helps to interpret autoregressive parameters (Getis and Aldstadt 2002).

III. STUDY AREA AND DATA

The data for this analysis pertain to South Korea. South Korea, which covers almost 10 million hectares in East Asia and has a population of approximately 47 million (Ministry of Land, Transport and Maritime Affairs 2008; Statistics Korea 2000), is comprised of 7 metropolitan cities and 8 provinces, which include 228 counties (or equivalent). This study uses four datasets at the county level: greenhouse gas emissions data in 1995, 2000, and 2005; forestland data in 1995, 2000, and 2005; boundary data in 2000; and environemntal feature data in 2000. Our final sample contains 228 counties after excluding the three islands farthest from the mainland (i.e., Jeju, Ongjin, and Ulleung). Definitions of the variables used in the regressions and detailed statistics are reported in Table 1.

Greenhouse gas emissions are measured by carbon dioxide equivalent (CO_2e). The CO_2e refers to the amount of carbon dioxide (CO_2) that would give the same global warming potential as the effect of the greenhouse gas or greenhouse gases being emitted. The CO_2e is normally used when attributing aggregate emissions from a particular source over a specified timeframe. The data used to calculate CO_2e were obtained from Emission Database for Global Atmospheric Research (EDGAR) (Janssens-Maenhout et al. 2010). Forestland data were acquired from Korean Forest Service (2009).

Census data, including population density, vacancy rate, per capita GDP, unemployment rate and rate of own-car commuting, were acquired from the Korean Statistical Information Service (KOSIS 2010). Among the census data, provincial per capita GDP and unemployment data were assigned to the counties within each province because they were only available at the provincial level. The boundary data, i.e., county and provincial boundaries, were provided by Korean Statistical Geographic Information Service (SGIS 2010). Elevation data were acquired from Environmental System Research Institute (ESRI 2006). Distance variables were created based on the boundary data using ArcGis 9.2 (ESRI 2010). These variables represent the distance between county centroids and either centroids of the nearest metropolitan city or the nearest point of the polylines representing seaside. The other environmental features of precipitation and temperature were acquired from Korean Meteorological Administration (KMA 2000).

The EDGAR retains levels of annual gross emissions, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), which are generally considered the major sources of greenhouse gas emissions. The data are derived from various human activities (e.g., manufacture, transportation, agriculture, and waste disposal) at the level of 0.1 × 0.1 degree in longitude and latitude (i.e., approximately 9 Km × 11 Km) every five years between 1970 and 1995 and every year from 2000 to 2005 (EDGAR 2010; Kirvan 1997). In this study, CO_2e was estimated by summarizing weighted values of CO_2, CH_4, and N_2O based on values of global warming potential (GWP) reported by the Intergovernmental Panel on Climate Change (IPCC). Specifically, $CO_2e = (CO_2 \times 1) + (CH_4 \times 21) + (N_2O \times 310)$, where the GWP weights for CO_2, CH_4, and N_2O are 1, 21, and 310, respectively. The GWP weights represent the global warming impact of CH_4 and N_2O relative to the impact of the same quantity of CO_2 over a 100-year time horizon. Among the three different time horizons (i.e. 20, 100, and 500 years) used in the GWP weights by the IPCC, the 100-year time horizon was adopted for the first commitment period of the Kyoto Protocol (2008-2012) and, thus, was chosen in the calculation of CO_2e in this study (IPCC 1995; Fearnside 2002). The GWP weights for each compound have been modified over the three IPCC assessment reports and the GWP weights introduced in the second assessment report were used in this study, which is also consistent with Kyoto Protocol.

The rates of deforestation during the periods of 1995-2000 and 2000-2005 were calculated based on forestland information for 1995, 2000, and 2005. Due to the jurisdictional reformation during 1995-2000 period, (1) forestlands in 1997 for five new counties in Ulsan metropolitan city (i.e., Ulsan Jung, Dong, Nam, Buk, and Ulju) were employed as proxies for forestlands in 1995 in these counties, and (2) forestlands in 1995 for the three counties (i.e., Yeosusi, Yeocheongun, and Yeochensi) that were merged into Yeosu county in 1998, were summed and used as forestland for Yeosu county in 1995. The 2000 census data were employed to represent initial socioeconomic conditions in explaining changes in deforestation and greenhouse gas emissions during the 2000-2005 period.

Meteorological measures of precipitation and temperature were observed from 68 stations throughout the country. Spatial interpolation has been commonly applied to produce meteorological measures across an area of interest when a limited number of observations were available only for some locations in the area (e.g., Xia, Winterhalter, and Fabian 1999). This method was applied to precipitation and temperature, with the interpolated measures assigned to the counties as proxy data. The elevation data were obtained from Environmental System Research Institute (ESRI 2006) and were calculated at a resolution of 1/3 arc-second or approximately 10 meters. Average elevation for each county was computed using the Zonal Statistics tool in ArcGIS 9.2 and was assigned to each county.

Forestland in South Korea is categorized under three ownership types: national, public, and private ownership (FAO 2000). Ownership of national, public, and private forestlands lies with the federal government, local governments, and private individuals, respectively. Because the Korean Forest Agency is a federal agent, the forestland purchased by Korean Forest Agency is categorized as national forestland. In 2009, 24%, 8%, and 68% of total forestland was categorized as national, public, and private forestland, respectively (Korean Forest Service 2009).[1]

IV. EMPIRICAL RESULTS

The choice of spatial weight matrices had an effect on the overall measure of fit for the first-stage deforestation model and second-stage greenhouse gas emission model (Table 2). The adjusted R^2s for the deforestation model range between 0.17 and 0.37, and the adjusted R^2s for the greenhouse gas emission model range between 0.36 and 0.43. The second-stage greenhouse

[1] The difference between national and public forestland is that national forestland is owned and managed by the federal government while public forestland is owned and managed by local governments.

gas emission model using the (row standardized) hybrid spatial weight matrix between the KNN (*k*=2) nearest neighbor weight matrix and the inverse distance weight matrix (hereafter referred to as "hybrid KNN(2)") has a higher adjusted R^2s than the models using the other spatial weight matrices. Given these results, the general spatial models were estimated using the hybrid KNN (2) specification.

First-Stage deforestation Model

The spatial lag AR coefficient was not significant at the 5% level, suggesting that the rate of deforestation was not spatially correlated. More densely-populated counties had lower deforestation rates. Deforestation, in general, occurs where population densities are low since large-scale forests preclude large-scale human settlements (Brown and Pearce 1994, p 156). As such, a county with lower population density tends to experience greater deforestation. Counties with greater vacancy rates and counties where unemployment rates were higher had greater deforestation rates. These findings imply close correlation between depressed economic conditions (i.e., high vacancy rate and high unemployment rate) and high deforestation rates. This result may be puzzling since we would expect a positive relationship between economic development and the deforestation rate in a newly industrialized country like South Korea, whereas significant amounts of deforestation are caused by subsistence activities of poor populations in the case of developing countries (Angelsen and Kaimowitz 1999; Tole 1998). Counties with greater rates of own-car commuting had greater deforestation rates. This finding is consistent with previous literature where a car-dependent commuting pattern is one of the underlying causes of deforestation due to road building (e.g., Chomitz and Gray 1996).

Temperature is the only environmental variable (i.e., elevation, distance to major city, distance to seaside, precipiation, and temperation) that has a significant effect on the deforestation rate. Counties with lower temperatures had greater deforestation rates. The negative effect of temperature may be explained by greater development pressure on forestland in northern South Korea where the ever-growing city of Seoul is located and the average temperature is lower than in southern South Korea.

Of particular interest is the coefficient associated with the percentage of national forestland. Counties with high percentages of national forestland had lower deforestation rates, suggesting that national forestland works well as a buffer for protecting forestland. Specifically, a 1% increase in the percentage of national forestland decreases the deforestation rate by 0.014%.

Second-Stage Greenhouse Gas Emission Model

The spatial lag AR coefficient was 0.49 and significant at the 5% level, suggesting that the change in greenhouse gas emissions was positively correlated, exhibiting positive spatial clustering. Counties with lower rates of own-car commuting had greater increases in greenhouse gas emissions. As the reason for the negative effect is not clear, further research is merited. Greenhouse gas emissions increased more in counties with higher elevations. This positive effect of elevation on greenhouse gas emissions may be related to increasing exploitation of high-elevation mountainous terrain for other than traditional uses. Specifically, land use that tends to generate more greenhouse gas emissions (e.g. industrial and residential uses, golf course development, and highway infrastructure) has increased drastically on high-elevation mountainous terrain while less emissions-intensive traditional uses (e.g. agricultural and military) have sharply decreased in such areas since the 1990's (Korean Forest Service 2010).

Counties closer to seasides had greater increases in greenhouse gas emissions. This positive effect of proximity to the nearest seaside may be related to the primary sources of CO_2 emissions (large-scale, fossil-fuel power stations) often being located on or nearby seasides in South Korea (e.g., Donghae, Honam, Samcheonpo, and Yeosu power plants). The time lag coefficient of percentage change in greenhouse gas emissions was positive and significant at the 5% level, suggesting that the change in greenhouse gas emissions had positive time-lag effects. This result reflects the time-lags inherent in greenhouse gas emissions, which also have been shown in previous literature (e.g., Stern and Kaufmann 1999; 2000).

Of particular interest is the positive and significant (5% level) coefficient associated with the predicted deforestation rate from the first stage. The positive effect confirms a previous finding that loss of forests is a significant contributor to greenhouse-gas emissions (e.g., Johnson 2009). Specifically, a 1% increase in the deforestation rate increases greenhouse gas emissions by 2.775%. That the percentage of national forestland is significant and negative in the first stage deforestation model, and the deforestation rate is positive and significant in the second-stage greenhouse gas emissions model is important, because increases in the percentage of national forestland incrementally reduce the deforestation rate, which in turn mitigates the percentage increase in greenhouse gas emissions in the simulations that follow.

Simulation of Percentage of National Forestland Increase on Greenhouse Gas Emissions

All three hypothetical scenarios resulted in mitgation of CO_2e emissions compared with the baseline scenario. Specifically, simulation under the hypothetical scenarios: (1) purchase forestlands in the descending order of greenhouse gas emissions per hactare in each county, (2) purchase forestland in the ascending order of forestland prices per hactare in each county, and (3) purchase the same amount of forestland in each county with some exceptions (see details in the subsection "Determining hypothetical percentage of national forestland") yielded lower increases in deforestation (0.67%, 0.57%, 0.71% for the scenarios (1), (2), and (3), respectively) than the observed percentage of national forestland (the baseline) (0.81%) (Table 4).

As a result, simulations under the hypothetical scenarios saved forestland (1,308 hectares, 28,403 hectares, and 2,127 hectares for scenarios (1), (2), and (3), respectively) compared with the baseline. Forestland saved for scenarios (1), (2), and (3) are respectively 4.3%, 9.4%, and 7.0% of the total deforested area in the baseline. These reductions in the deforestation rate due to increased percentages of national forestland resulted in mitigating the increase in CO_2e by 20 million tons, 18.5 million tons, and 18.6 millions tons for scenarios (1), (2), and (3), respectively, compared with the baseline. Reductions in CO_2e are respectively 33%, 31%, and 31% less than total greenhouse gas emissions in the baseline, and they represent 4.1% to 4.5% reductions in annual emissions, compared with 446 million tons of CO_2e emmisions for all of South Korea in 2000.

V. CONCLUSION

This research analyzed the effects of forestland ownership conversion on greenhouse gas emissions by quantifying the relationship between forestland ownership conversion and deforestation and then examining the effects of the resulting change in deforestation on greenhouse gas emissions in South Korea. The research shows that the increased percentage of national forestland mitigated the increase in the deforestation rate, which in turn resulted in mitigating the increase of greenhouse gas emissions (measured as a carbon dioxide equivalent

CO_2e). This finding suggests that the long-term plan to purchase private forestland will support achieving South Korea's voluntary target of reducing emissions.

The *ex ante* simulations forecast greenhouse gas emissions resulting from deforestation rates under the current level of national forestland and under three scenarios of increased percentages of national forestland that include hypothetical purchases of private forestland by the Korean Forest Service (with a $7.5 billion budget) under their long-term acquisition plan. Of the three purchasing scenarios, purchasing forestlands in the descending order of greenhouse gas emissions per hactare in each county (scenario (1)) resulted in the greatest mitigation of CO_2e emissions while saving the least amount of forestland, compared with the baseline. On the other hand, purchasing forestlands in the ascending order of forestland prices per hactare in each county (scenario (2)) resulted in saving the most forestland while producing the least mitigation CO_2e emissions, compared with the baseline.

The goal of the Korean Forest Service's long-term plan is to decrease the rate of deforestation by increasing the portion of national forestland for the expansion of carbon sinks. Because the details of where the Korean Forest Service plans to spend its $7.5 billion budget to purchase private forestlands have not been publicized to prevent land speculation, implementation of the long-term plan is unclear. Thus, how well the long-term plan can be achieved and carbon sinks expanded depends on how effectively its budget is used to buy private forestlands. The results from the *ex ante* simulations imply that purchasing forestlands in the descending order of greenhouse gas emissions per hactare in each county seems to be the best strategy among the three scnearios because it can potentially mitigate CO_2e emissions the most, given the budget.

An important caveat to mention is that the effects of forestland ownership conversion on greenhouse gas emissions were quantified in this research by modeling the effects of ownership conversion on the deforestation rate, which in turn affects CO_2e emissions. This modeling effort did not account for the effect on greenhouse gas emissions of forest carbon sequestration that would result from decreasing the deforestation rate, suggesting that the simulated scenarios underrepresent the true effects on CO_2e emissions.

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TABLE 1

VARIABLE NAMES, DESCRIPTION, AND DESCRIPTIVE STATISTICS

Variable	Description	Mean	Std. Dev.
Rate of deforestation	Ratio of deforested land during 2000-2005 to forestland in 2000 (%)	0.796	1.775
Percentage change in greenhouse gas emissions	Ratio of percentage change in carbon dioxide equivalent (CO_2e) during 2000-2005 to carbon dioxide equivalent in 2000 (%)	-0.249	7.505
Simulation variable			
Percentage of national forestland†	Ratio of nationally owned forestland to the total forestland in 2000 (%)	19.041	27.659
Socioeconomic variable			
Population density	Population per hectare in 2000 (population per hectare)	39.919	64.141
Vacancy rate	Ratio of vacant houses to total houses in 2000 (%)	5.825	3.101
Per capita GDP	Gross regional domestic product per person for provincial level in 2000 ($1,000 per person)	11.055	2.578
Unemployment	Ratio of unemployed to the labor forces, ages 15 or older in 2000 (%)	4.064	1.211
Rate of own-car commuting	Ratio of own-car commuters to total commuters in 2000 (%)	24.467	8.868
Environmental variable			
Elevation	Average elevation (feet)	566.716	504.685
Distance to city	Distance to the nearest metropolitan city (mile)	28.257	24.146
Distance to seaside	Distance to the nearest seaside (mile)	19.375	17.030
Precipitation	Annual gross precipitation (inches)	50.420	5.912
Temperature	Average temperature in 2000 (°C)	12.131	1.151
Time and Lag variable			
Lagged rate of deforestation†	Ratio of deforested land during 1995-2000 to forestland in 1995 (%)	1.477	7.325
Lagged percentage change in greenhouse gas emissions	Ratio of percentage change in carbon dioxide equivalent (CO_2e) during 1995-2000 to carbon dioxide equivalent in 1995 (%)	6.686	14.832

† Unique instrumental variables in the first-stage regression, deforestation model.

TABLE 2

MODEL SELECTION CRITERIA

Spatial Weighting Matrix	Adjusted R^2 (First stage)	Adjusted R^2 (Second stage)
Queen Contiguity Orders		
Queen Contiguity (Order 1):	0.37	0.36
Queen Contiguity (Order 2):	0.23	0.38
Queen Contiguity (Order 3):	0.17	0.39
K nearest neighbors of order q [*KNN*(*q*)]*:*		
KNN(*2*) = 2	0.18	0.40
KNN(*3*) = 3	0.24	0.37
KNN(*4*) = 4	0.22	0.39
Inverse distance neighborhoods	0.23	0.41
Inverse distance neighborhoods:		
Queen Contiguity(1) × inverse distance	0.28	0.36
Queen Contiguity(2) × inverse distance	0.24	0.38
Queen Contiguity(3) × inverse distance	0.23	0.38
KNN(*2*) = 2 × inverse distance	0.17	0.43
KNN(*3*) = 3 × inverse distance	0.18	0.42
KNN(*4*) = 4 × inverse distance	0.17	0.43

TABLE 3
REGRESSION RESULTS

Variables	Deforestation model (LHS = Rate of deforestation)		Greenhouse gas emission model (LHS = Percentage change in greenhouse gas emissions)	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Intercept	1.678	2.669	29.176*	10.386
Endogenous variable				
Rate of deforestation			2.775*	1.328
Simulation variable				
Percentage of national forestland†	-0.014*	0.006		
Socioeconomic variable				
Population density	-0.007*	0.003	-0.007	0.013
Vacancy rate	0.098*	0.050	0.022	0.200
Per capita GDP ($\times 10^{-3}$)	0.025	0.048	0.005	0.131
Unemployment	0.671*	0.215	-0.964	0.932
Rate of own-car commuting	0.049*	0.015	-0.311*	0.082
Environmental variable				
Elevation	-3.584	1.905	22.358*	8.741
Distance to City	0.005	0.008	-0.039	0.024
Distance to Seaside	-0.011	0.009	-0.046*	0.024
Precipitation	0.006	0.021	-0.087	0.059
Temperature	-0.406*	0.148	-0.758	0.508
Time and spatial lag variable				
Lagged rate of deforestation †	0.040	0.021		
Lagged percentage change in greenhouse gas emissions			0.241*	0.032
Spatial lag	-0.047	0.176	0.486*	0.103
Spatial error	-0.016	0.048	-0.408*	0.069

* Significant at the $\alpha = 0.05$ level (5%).
† Unique instrumental variables in the first-stage regression, deforestation model.

TABLE 4

SIMULATION OF PERCENTAGE OF NATIONAL FORESTLAND INCREASE ON GREENHOUSE GAS EMISSIONS

Scenario	Average rate of deforestation (%)	Total deforested area (hectare)	Total mitigated deforested land by the purchasing scenarios, compared with baseline (hectare)	Average percentage change in greenhouse gas emissions (%)	Total increased greenhouse gas emissions (ton)	Total mitigated increase in greenhouse gas emissions, compare with basline (ton)
Baseline	0.81	30,209		11.38	59,951,364	
Scenario 1	0.67	28,901	1,308	7.43	39,697,863	20,253,501
Scenario 2	0.57	1,805	28,403	7.16	41,369,743	18,581,621
Scenario 3	0.71	28,081	2,127	7.52	41,338,769	18,612,595

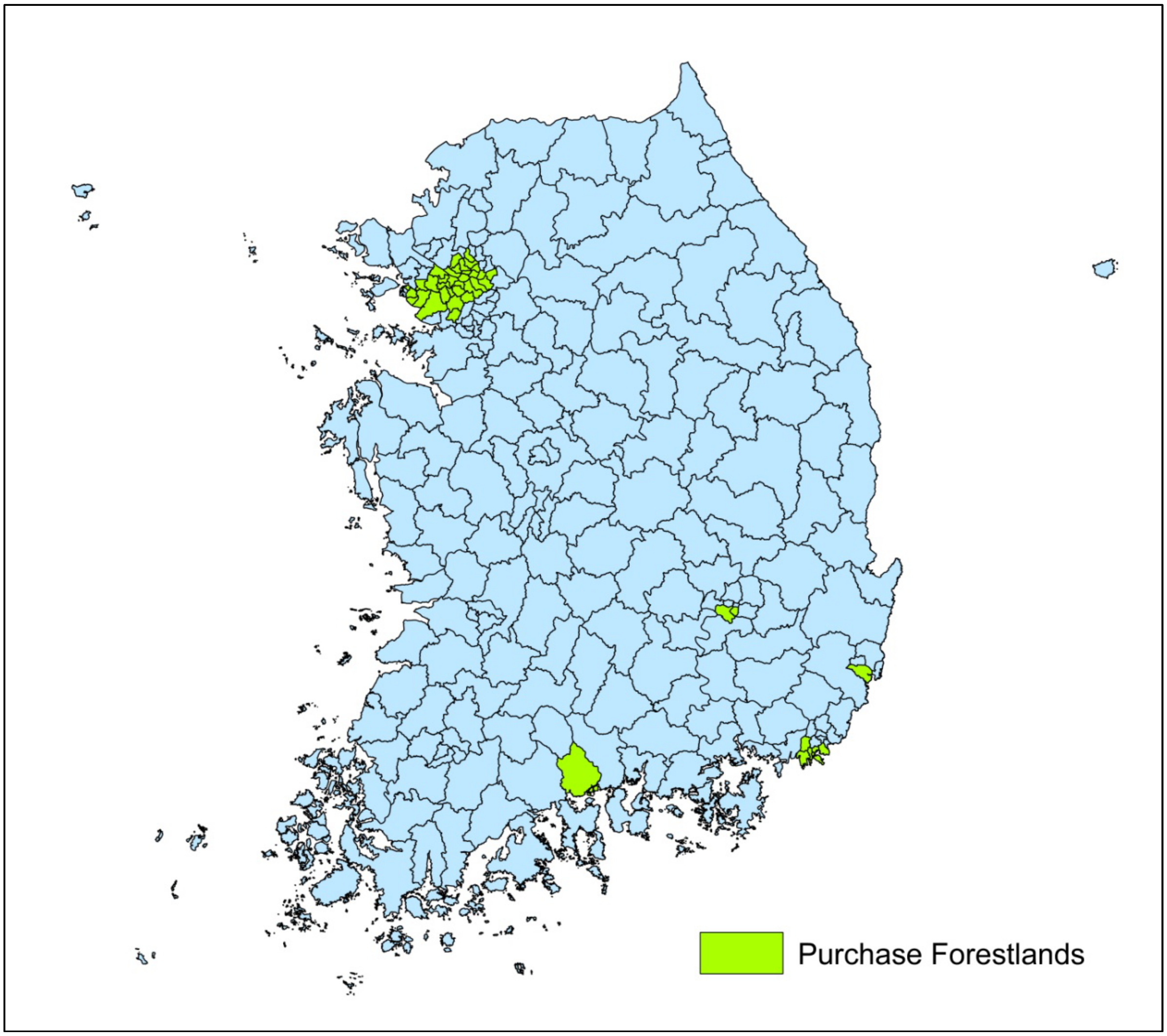

FIGURE 1
Scenario (1): PURCHASE FORESTLAND IN DESCENDING ORDER OF GREENHOUSE GAS EMISSIONS IN EACH COUNTY

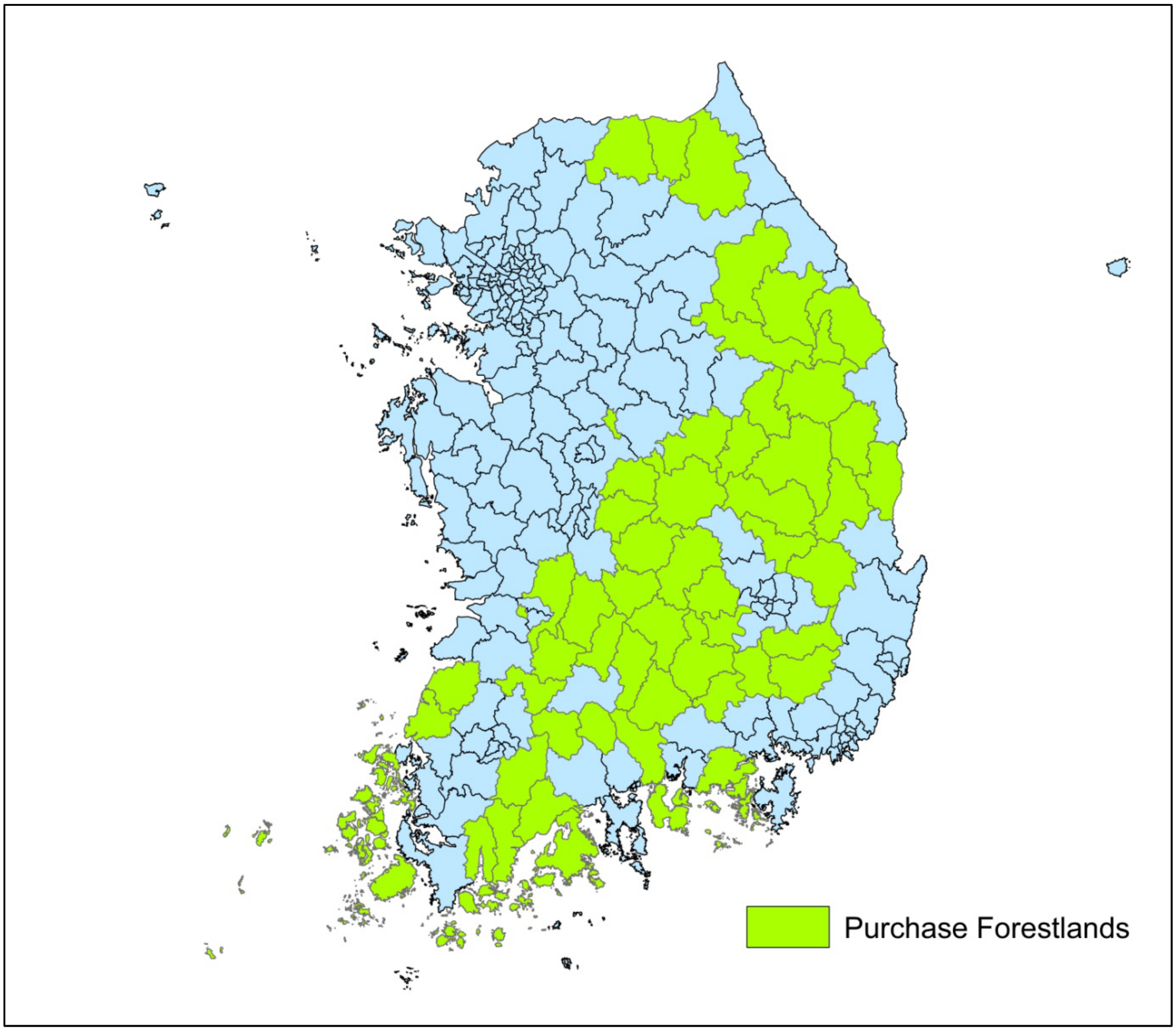

FIGURE 2
Scenario (2): PURCHASE FORESTLANDS IN ASCENDING ORDER OF FORESTLAND PRICE IN EACH COUNTY

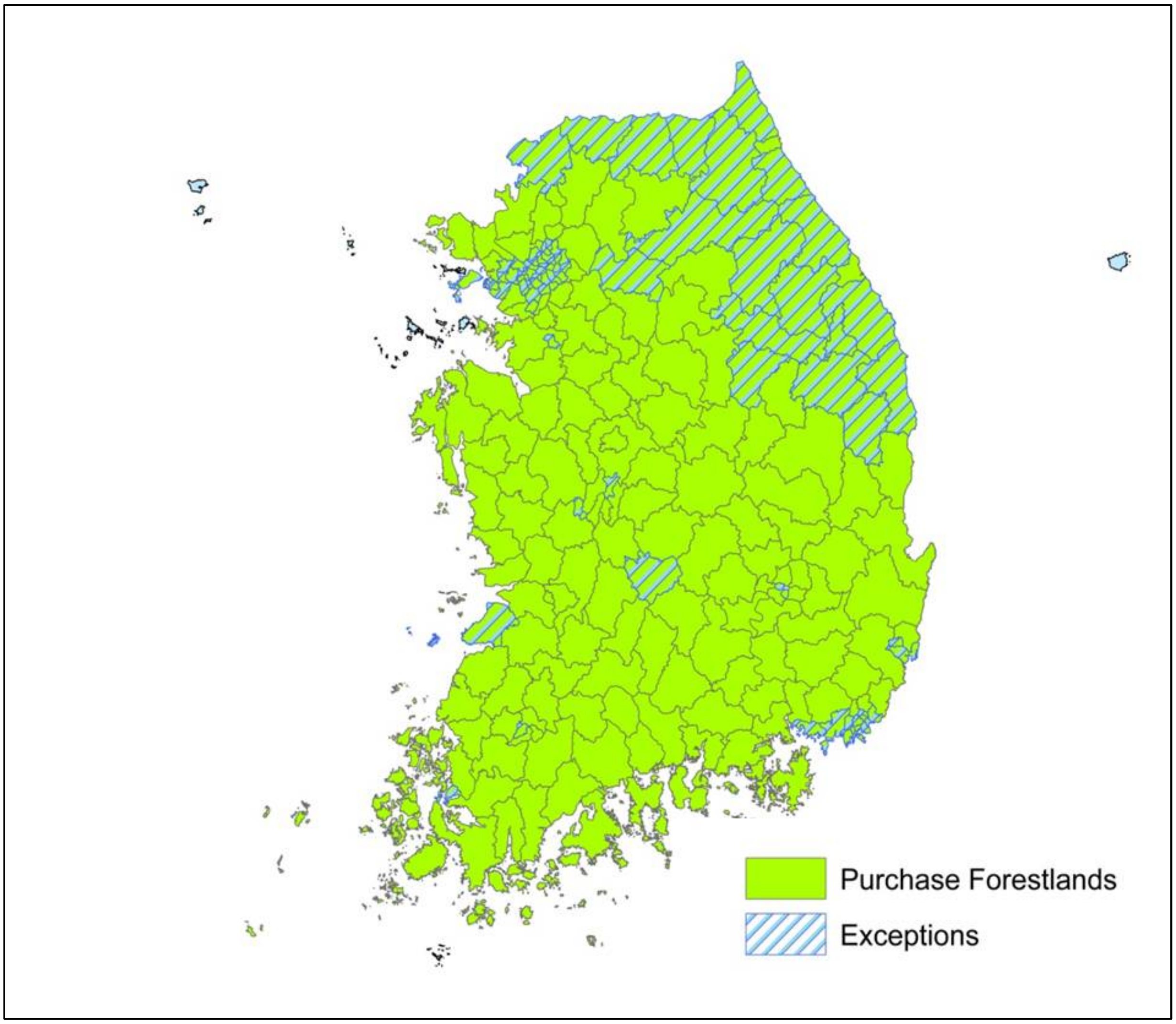

FIGURE 3
Scenario (3): PURCHASE THE SAME AMOUNT OF FORESTLAND IN EACH COUNTY WITH SOME EXCEPTIONS (SEE DETAILS IN THE SUBSECTION, "DETERMINING HYPOTHETICAL PERCENTAGE OF NATIONAL FORESTLAND")

Footnotes

1. The average exchange rate in 2010 (1,176 Korean Won for $1) was used and rounded to 10 million dollars. The same exchange rate was applied for the calculation of the budget to purchase private forestland throughout the paper.

2. While the Rook contiguity is measured based on a shared border and the Bishop contiguity is measured based on a shared vertex, the Queen contiguity incorporates both the Rook and Bishop relationships into a single measure.