Leaf Area Index (LAI) Analysis of Landsat Satellite Images for Monitoring of the Future CDM Afforestation/Reforestation Project in North Korea

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FOREWORD

Global warming is one of the most urgent environmental problems we the humankind face now. As an effort to solve the global warming problem, CDM Afforestation / Reforestation project is proposed to remove the Green House Gas (GHG) from the atmosphere. CDM A/R project requires a vast area to plant trees to sink carbon, so most sites proposed CDM A/R project are limited to atropical/tropical regions. But, due to the mismanagement of agricultural land and the economic failure, North Korea forest have been deforested significantly for the last several decades, thus the vast once-forested bare land of North Korea is expected to be an ideal site for the CDM A/R project of South Korea.

In the preparation of CDM A/R project, accurate information of the historical change and the current status of North Korea forest is exceptionally important, but it is also difficult to have without remote sensing technology. Among many vegetation-related parameters, Leaf Area Index (LAI) is widely used to estimate forest photosynthetic activity and biomass by using remotely sensed imagery. Forest monitoring based on remotely sensed LAI data is a useful methodology for the effectiveness analysis of CDM A/R project in North Korea where the accessibility is significantly limited and little data is available in South Korea.

Due to these difficulties, few studies have attempted to model the change of photosynthetical activity of North Korea forest by using satellite imagery. Thus it is required to test the feasibility of remotely sensed LAI modeling of North Korea forest. The Geocomputational LAI modeling of Landsat/MODIS satellite imageries provides valuable information for policy-makers and CDM project managers to prepare CDM A/R project in North Korea.
I would like to express my sincere gratitude to principal investigator of this research, Dr. Sangbum Lee, and research participants, Ms. Hyun-Jung Hong, for their hard work and scholarly endeavors. Many thanks go to the members of the advisory committee, Dr. Yowhan Son (Korea University) and Dr. Seung-Ho Lee So (Korea Forest Research Institute) for their valuable suggestion and comments. I would also like to extend my appreciation to Dr. So-Eun Ahn and Dr. Paikho Rho in the Korea Environment Institute for their critical reviews and helpful discussion of this research. Finally the peer reviews by three anonymous referees were very helpful in evaluating this manuscript from an unbiased perspective.

Suh Sung Yoon
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Abstract

The Kyoto Protocol is the result of international efforts to minimize global warming by reducing the greenhouse gas emission and developing CDM (Clean Development Mechanism). LULUCF (Land-Use, and Land-Use Change and Forestry) activities which include Afforestation, Reforestation, Forest Management are proposed for CDM project. Thus LULUCF activities are mainly about the land use/land cover change, and the accurate LU/LC map is extremely important to verify the validity of LULUCF activities. Remote sensing technology can be used to analyze the effect of a landscape change on a global carbon budget by estimating the Leaf-Area-Index (LAI) of satellite imagery because the spectral characteristics of a forest are determined by the leaf shape and arrangement of a tree canopy.

As North Korea has experienced intensive deforestation for last few decades, the CDM Afforestation/Reforestation project in North Korea would be a great opportunity to restore the significantly degraded environment of North Korea. The main research objective is to analyze the forest land cover change and the LAI change on the forest cover between 1990 and 2002 Landsat images to test the feasibility of a LAI modeling of the past Landsat images based on the current reference data set (MODIS LAI/fPAR image and in situ LAI) and SOM (Self-Organizing Map)-based geocomputational algorithm as a better monitoring methodology of CDM Afforestation / Reforestation project in North Korea. The results of this study show the continuous destruction of North Korea forest and the applicability of the scaling-up LAI modeling from in situ LAI and the scaling-down LAI modeling from MODIS LAI/fPAR image. The forest cover of the study area, a Landsat image (Path 117, Row 33), have been reduced from 1990 to 2002 and the modeled LAI values of 2002 Landsat are lower than that of 1990 Landsat. The applicability of SOM-based geocomputational method for the scaling-up/down LAI modeling of Landsat image is proved as all three output images show consistent results.
The Landsat imageries used in this study are thoroughly preprocessed to remove the atmospheric/topographic distortions of the spectral reflectance of Landsat imagery by using MODTRAN and SCS+C algorithms. The WDVI comparison for the LAI change analysis is not a direct LAI modeling, but is an indirect LAI modeling based on the theoretical assumption of linear relationship between in situ LAI and WDVI validated in the previous study. The in situ LAI data is collected in Kwang-Neung Forest of South Korea by using LAI-2000 PCA, so the in situ LAI modeling of Landsat image is based on a reference data not collected in North Korea forest. Only the MODIS-based LAI modeling is a direct LAI modeling methodology based on the reference data estimated in the study area. The significant finding of this study is that the methodologies tested in this study show a consistent result, despite of the different theoretical assumption and reference data set.

Due to the limited availability of the reference data of the study area and the few sampling points of in situ LAI from Kwang-Neung Forest, this study evaluates the feasibility of the scaling-up/-down LAI modeling based on in situ LAI and MODIS LAI. The next study should elaborate the scaling-up/-down LAI modeling with more comprehensive reference data of North Korea forest and attempt to differentiate deciduous and coniferous forest and then model the expected LAI value separately. In the actual CDM A/R project of North Korea, the full accessibility to North Korea forest is expected, so more accurate LAI modeling would be possible with more on-site measurements of reference data including in situ LAI. This study will help the policy-makers and CDM project managers in the preparation of Afforestation/Reforestation project in North Korea by providing the information of the historical carbon cycle of North Korea forest and empirically tested monitoring methodology of the expected carbon sink from the CDM A/R project of North Korea.
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Chapter 1. Introduction

The global warming is not a scientific dispute anymore, but is a scientific fact. Despite few brownlash scientists try to diminish the effect of the greenhouse gas on the global warming, most scientists do not question that the greenhouse gas emission causes the global warming. The CO₂ in atmosphere has increased about 25% during 20th century and continues to increase in part due to fossil fuels and landscape change.

The Kyoto Protocol come from international efforts to minimize the effect of global warming by reducing the greenhouse gas emission and developing CDM (Clean Development Mechanism). To diminish the effect of greenhouse gas, the Kyoto Mechanism defines three market mechanisms: Join Implementation (JI), Clean Development Mechanism (CDM), and International Emission Trading (IET). CDM (Clean Development Mechanism) adopts diverse projects to reduce greenhouse gas (GHG) emission and sink GHG. LULUCF (Land-Use, and Land-Use Change and Forestry) activities which include Afforestation, Reforestation, Forest Management are proposed for CDM project. The basic idea of LULUCF activities is to sink greenhouse gas, e.g. CO₂ in forest by converting non-forest land use/land cover area into forest land cover area and managing forest to sink more carbon. Thus LULUCF activities are mainly about the land use/land cover change, and the accurate LU/LC map is extremely important to verify the validity of LULUCF activities.

According to UNFCCC, activities in the LULUCF sector can provide a relatively cost-effective way to offset emissions, either by increasing the removals of greenhouse gases from the atmosphere (e.g. by planting trees or managing forests), or by reducing emissions (e.g. by curbing deforestation). However, there are drawbacks as it may often be difficult to estimate greenhouse gas removals and emissions resulting from activities of LULUCF. In addition, greenhouse gases may be unintentionally released into the atmosphere if a sink is damaged or destroyed by a forest fire or disease.

Under Article 3.3 of the Kyoto Protocol, Parties decided that greenhouse gas removals and emissions through certain activities — namely, *afforestation*
and reforestation since 1990 — are accounted for in meeting the Kyoto Protocol’s emission targets. Conversely, emissions from deforestation activities will be subtracted from the amount of emissions that an Annex I Party may emit over its commitment period. Under Article 3.4 of the Kyoto Protocol, Parties could elect additional human-induced activities related to LULUCF, specifically, forest management, cropland management, grazing land management and revegetation, to be included in its accounting for the first commitment period.

As mentioned, the LULUCF activities require accurate information of the past and current land use of the target landscape where LULUCF will be implemented. This information is effectively acquired using remote sensing techniques. In fact, the most accurate field survey data on the past date is usually not available for many target areas. Thus the archived aerial photograph or satellite imagery provide useful information about the past land cover type of the target landscape. For this reason, remote sensing technology including aerial photograph and satellite imagery are recommended as an official tool to verify the land use of the target area before 1990 and to select a suitable area for afforestation/reforestation.

As the Kyoto Protocol deals with the increasing greenhouse gas emission, it is required to have accurate information of a global carbon balance. In addition, the CDM-LULUCF activities are closely related to a global carbon circulation. In a global carbon budget, the role of temperate forest as a carbon sink is well known, but it is relatively difficult to estimate the carbon sink of temperate forest. In addition to the role of temperate forest as a carbon sink in a global carbon balance, the landscape change of tropical and tundra forest needs to be estimated to have an accurate global carbon budget model. Remote sensing technology can be used to analyze the effect of a landscape change of a global forest on a global carbon budget by estimating the Leaf-Area-Index (LAI) of remotely sensed image.

The reason of estimating LAI from remotely sensed imagery is to model accurate global carbon budget using biogeochemical models, i.e. BIOME-BGC. In biogeochemical models, LAI is a key factor to model carbon uptake and sink in soil by forest. Although a biogeochemical modeling is not the research object of this study, the estimated LAI of this study can be used for a biogeochemical modeling in the future study and shows a general trend of
forest activity change over the last two decades. While the A/R forestation projects of CDM-LULUCF activities require accurate information of a land use change, the forest management project requires information of forest photosynthetic activity based on LAI estimates. Thus each project of CDM-LULUCF activities needs different landscape data: LU/LC map for the A/R forestation and LAI estimates for the forest management.

LAI is defined as m² in leaf per m² of ground (Pierce and Running 1988, Lymberner et al. 2000) and is useful in ecosystem analysis because of its importance in gas, water, carbon, and energy exchange with the atmosphere (Fassnacht et al. 1997, Ghotz et al. 1997). Despite its importance, the current methods of in situ LAI measurement are labor intensive and inappropriate to monitor landscape scale LAI. In remote sensing, the spectral characteristics of a forest are determined by the leaf shape and arrangement of a tree canopy, thus LAI is the most appropriate characteristic of a forest for remote sensing-based biomass estimation.

Diverse researches have been tried to estimate LAI from remotely sensed image. The fundamental way of remote sensing derived LAI measurement is to correlate in situ LAI and vegetation indices such as NDVI (Liu and Huete 1995, Jensen 2000, Lymburner et al. 2000). While many studies confirm the correlation of NDVI and LAI, some studies pointed out the threshold problem of NDVI-based LAI estimation because NDVI fails to increase in relation to increased LAI (Carlson and Ripley 1997, Lawrence and Ripple 1997, Datt 1998).

Although it is not accepted as an eligible CDM activity in the Marrakech Accords, deforestation avoidance is actively discussed and sustainable forest management (SFM) is suggested as a valid CDM project to avoid deforestation because one third of global greenhouse gas emission is accounted by deforestation in developing countries. Deforestation is not a temporal catastrophe, but a continuous environmental degradation. Thus a continuous monitoring of deforestation is a crucial methodology for an effective sustainable forest management (SFM). While deforestation in tropical region comes from intensive development for timber industry, the deforestation of temperate forest in North Korea is mainly caused by the failure of agriculture and forest policies. The deforestation of North Korea is alarming and need to be restored for a sustainable development.
For a better carbon management and policy, our main objective is to map LAI change in North Korea forest between 1990 and 2002 using remote sensing and GIS to examine the relationship between landscape change and the forest biomass by inferring a LAI value of Landsat data from *in situ* LAI measurement and MODIS LAI data. This study analyzes the land use change and the forest activity change of North Korea between 1990 and 2002 to quantify deforested area extent for the A/R project of CDM-LULUCF activities and the forest status for the forest management project of CDM-LULUCF. A hard-classified Land Cover maps are created from Landsat ETM imagery for year 2002 and used to assess the land cover change over the last twelve years. The LAI values of Landsat TM/ETM⁺ are modeled from coarse resolution MODIS LAI/fPAR data by scaling-down process and from detailed *in situ* LAI measurements by scaling-up process. I expect that this study will show a general deforestation trend and the feasibility of analyzing photosynthetic activity change of North Korea temperate forest to provide scientific information to plan a valid project of CDM-LULUCF activities. This research is mainly based on the use of NASA systems (e.g., Landsat and MODIS) to measure and monitor carbon sequestration in terrestrial ecosystem where the major and direct human-induced landscape disturbance takes place.
Chapter 2. Background and Research Objectives

Unprecedented rapid landscape change in a global scale makes it difficult to measure the total carbon volume of a terrestrial ecosystem. Before a satellite image was available, it was impossible to monitor the global ecosystem. The development of satellite remote sensing enhances our capability to monitor global ecosystem and provides a great opportunity of an effective global ecosystem modeling and management.

Most prior studies of environmental change using digital change detection techniques have involved data differences, classification operations which combine the change detection and change identification aspects of using change information to update resource surveys, and other techniques. Lambin and Strahler (1994) described two approaches to multitemporal remote sensing: comparative analysis of independent classifications, and simultaneous analysis of multi-temporal data. Comparative analysis of independent classification is an extension of classic paper map-based techniques. It is particularly valuable to analyze discrete cover classes (for example forested versus clear-cut), and lends itself to Markov transition analysis, for example in succession analysis (Hall et al., 1991).

There have been many studies regarding land-cover, vegetation and wetland change, and classification using remotely sensed data (Jensen et al., 1986; Allum and Dreisinger, 1986; Ackleson and Klemas, 1987; Jensen et al., 1987; Airola and Vogel, 1988; Achard and Blasco, 1990; Jensen et al., 1995; Hewitt and Cetin, 1999). Most studies related to environmental change using digital change detection techniques have been very successful for large areas (King et al., 1995). However, some failed to detect environmental changes at local and regional scales.

Leaf Area Index is an important parameter of a forest that is directly related to the photosynthesis, evapotranspiration, and the productivity of plant ecosystem (Bonan 1993). Direct in situ measurement of LAI is a labor intensive and destructive method, so it is only appropriate for a local scale study. The LAI estimation of remotely sensed image has been tried continuously and achieved limited successes (Turner et al. 1999). The NDVI is the most widely
used remote sensing data for LAI estimation, but is suffered from the saturation problem of high LAI value (Chen and Cihlar 1996; Carlson and Reley 1997, Lawrence and Ripple 1997, Datt 1998). Many external factors affect the LAI modeling of remotely sensed data, such as vegetation type, canopy structure, background, atmospheric condition, and topographic condition (Tian et al. 2000, Panferov et al. 2001). Most remotely sensed LAI studies use linear regression methodology to infer LAI value from remote sensing data (Liu and Huete 1995, Jensen 2000, Lymburner et al. 2000, Kim and Lee 2004), but artificial neural network has evaluated and showed a good accuracy (Jensen and Binford 2004).

As the LAI is difficult to be measured directly from satellite data, many studies have tried to infer LAI from vegetation indices. As stated above, NDVI has a poor correlation problem and a saturation problem in LAI estimation. Thus the accurate LAI estimation of remotely sensed imagery requires the development of new methodology. In order to achieve this objective, this study evaluates three different remote sensing algorithms to infer LAI of temperate forest and to test the feasibility of LAI modeling of the past satellite imagery by using the present LAI reference data.

The main research objective of this study is to analyze the forest land cover change and the LAI change on the forest cover between 1990 and 2002 Landsat images to test the feasibility of a LAI modeling of the past Landsat images based on the current reference data set (MODIS LAI/fPAR image and In Situ field-measured LAI) and SOM-LVQ neural network geocomputational method as a better monitoring methodology of CDM Afforestation/Reforestation project in North Korea. Specifically, this study wants to establish a noble remote sensing/GIS methodology for a scaling-up modeling of LAI from ground surveys to moderate resolution Landsat ETM and a scaling-down modeling of LAI from global (coarse resolution MODIS image) to regional (medium resolution Landsat image) to verify the accuracy of the LAI modeling of two different reference data set.

According to this research objective, this study is composed of three main research parts:
I. Estimating the forest land cover change of North Korea over the last twelve years

Clean Development Mechanisms (CDM) in the forestry-sector are afforestation, reforestation, and forest management. Afforestation or reforestation project activities need to define the target area where afforestation or reforestation will be implemented. Although the degraded land for A/R CDM is defined a land that is unforested in 1990, it is needed to monitor the continuous land cover change from 1980’s. In this study, I do not specifically estimate an area extent of A/R CDM project activity, but analyze the forest land cover change of North Korea over the last twelve years. A simplified land cover map (forest vs. non-forest) is created from the atmospherically / topographically corrected Landsat imagery to compare the forest area between 1990 and 2002 Landsat images (Path 117, Row 33). Conventional Maximum-Likelihood hard classification is used to create the simplified forest cover map.

II. Modeling LAI value of a medium spatial resolution Landsat satellite image from WDVI, In Situ measurement and MODIS LAI/fPAR data

In addition to the estimation of forest land cover change, the forest photosynthesis activity change over the last two decades is analyzed by forest Leaf Area Index (LAI). Forest management in North Korea will be counted as a CDM project activity of South Korea, and, at the same time, it is another important aspect of the South-North Korea cooperation to maintain environmental sustainability. To understand the current forest condition of North Korea, it is better to understand the historical change of the forest photosynthesis activity based on historical satellite imagery.

Various forest-related satellite indices are available, but LAI is widely used to analyze the forest activity with fPAR (fraction of Photosynthetically Active Radiation) and one of the key factors in forest NPP modeling. As it is extremely difficult to visit the forest area in North Korea to measure in situ LAI, I have used the field measured LAI in South Korea to model LAI value.
from satellite image. In addition to the direct correlation analysis of in situ LAI and multispectral satellite image, I use two different data sets to model the forest LAI of Landsat data: in situ LAI measurement and MODIS LAI/fPAR. While Landsat image is used as input data of the LAI modeling, in situ LAI and MODIS LAI data sets are used as output data of the LAI modeling.

**Vegetation Related Remote Sensing Data for LAI Modeling:**

The phenological state of vegetation and background spectral properties have a significant impact on LAI retrievals from remote sensing based algorithms. Background reflectance properties are important for LAI calculations of sparse canopies, such as crops, grass and shrubs. Previous studies have shown that LAI retrieval using NDVI had lower $R^2$ values, between 0.52 and 0.89 (Baret et al., 1993; Nemani et al., 1993). One of the studies showed that middle infrared (MIR) corrected NDVI better represented LAI for a watershed in Montana (Nemani et al., 1993). One of the reasons that the relation between a simple NDVI and LAI is poorly defined at TM scale is the outsized contribution of understory vegetation and background materials to the near infrared reflectance in open canopies. The MIR correction factor as a scalar for canopy closure scales down the inflated NDVI in open canopies and results in an improved relation between modified NDVI and LAI. In the LAI modeling of remotely sensed data, NDVI has been used in many studies because it is the most widely used vegetation-related indices of remotely sensed data. Despite its popularity, NDVI has a critical shortcoming, a saturation problem in a high LAI value, so the relationship of NDVI and LAI is not linear. Thus a LAI modeling based on a linear regression is not expected to provide an accurate LAI estimate of satellite data.

When it comes to the other satellite sensors, such as ASTER or MODIS, the spectral resolution is much higher than Landsat, so the vegetation-related information contents should be much higher than Landsat. To utilize this enhanced spectral information, the other vegetation indices should be developed and evaluated in LAI modeling, or the original band information can be used in LAI modeling. In case of MODIS, enhanced vegetation index (EVI) has been proposed by The MODIS Land Discipline Group.
\[ EVI = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + C1 \rho_{\text{red}} - C2 \rho_{\text{blue}} + L} \]

\( \rho_{\text{nir}} \) = NIR reflectance
\( \rho_{\text{red}} \) = Red reflectance
\( \rho_{\text{blue}} \) = Blue reflectance
C1 = Atmosphere Resistance Red Correction Coefficient, 6
C2 = Atmosphere Resistance Blue Correction Coefficient, 7.5
L = Canopy Background Brightness Correction Factor, 1
G = Gain Factor, 2.5

Unlike rational vegetation indices, Tasseled Cap transformation is to reproject the feature space of satellite data into a new orthonormal basis for the bands that highlights differences in vegetation and soil. The Tasseled Cap transformation for Landsat image defines Brightness, Greenness, Wetness, and Haziness. Among the new 4 bands, Greenness and Wetness can be used for LAI modeling. In addition to the Tasseled Cap transformation matrix of Landsat, the Tasseled Cap transformation matrixes of IKONOS, ASTER, and MODIS are estimated, but few studies have tried to apply the Tasseled Cap transformation in LAI modeling.

Although the vegetation indices and the Tasseled Cap transformation are useful remotely sensed data in vegetation study, these bands just accentuate the difference between vegetation and non-vegetation land cover types and do not provide additional information. Thus it might be better to use the original band information. If the LAI modeling is based on a linear regression, the simplified NDVI or Tasseled Cap band may be better than the entire bands of a satellite sensor for a LAI modeling. But it may be too optimistic to expect a high accuracy of the linear regression of in situ LAI and a single vegetation-related band (NDVI or Tasseled Cap).

In this study, WDVI (Weighted Difference Vegetation Indices) is used to infer the LAI value of Landsat pixels because the WDVI calculated from surface reflectance of Landsat image show the most strong linear relationship with the in situ LAI reference data than other vegetation indices (Fang and Liang 2003)(Figure 7–8). It will be further discussed in the next chapter.
**In Situ LAI Measurement**

The *In Situ* LAI is estimated by the Gap-Fraction analysis in order to reduce labor/time-intensive traditional destructive harvesting *in situ* measurement. Gap fraction theory estimates LAI by measuring the decrease of light intensity through tree canopy.

\[ \frac{IL}{IO} = e^{-kL(L)} \]

where \( IL/IO \) is the percentage of incident light at the top of the canopy reaching depth \( L \) in the canopy, \( LAI(L) \) is the cumulative LAI from the top of the canopy to point \( L \), \( k \) is a stand or species specific constant, and \( e \) is the base of natural logarithms (Larcher 1975, Aber and Melillo 1991). The principal factor controlling the \( k \) coefficient is the mean leaf inclination angle characterizing the canopy, and forest canopies typically exhibit \( k \) values for 0.5 (Aber and Melillo 1991).

The LAI-2000 PCA (Plant Canopy Analyzer) from LI-COR is used to measure the gap-fraction method. The LAI-COR 2000 calculates LAI from radiation measurements made with a “fish-eye” optical sensors (148° field-of-view) with an optical filter that only transmits ultraviolet to blue wavelengths (380-490 nm). Measurements made above and below the canopy are used to determine canopy light interception at 5 angles (7°, 23°, 38°, 53°, AND 68°) from which LAI is computed using a model of radiative transfer in vegetative canopies. The method is based on the empirical relationship between the quantity of leaf area and the penetration of diffuse radiation through the canopy. LAI estimation is based on the following assumptions: (1) the foliage blocks or absorbs all the light in the spectrum of 490 nm and less, (2) the canopy elements are much smaller than the projected surface area of each concentric ring, and (3) the foliage is distributed randomly with respect to azimuth (Fournier et al. 2003). The effective LAI is extracted from the matrix inversion of the gap fraction values following Campbell and Norman (1989). The limitation of this method is to acquire reference data, which may require the installation of scaffolding for above-canopy access or finding a significant clearing close to the measurement site.

The *in situ* LAI data used in this study was measured at Kwang-Neung
Forest on August and September 2002. Due to the limited number of the LAI sampling points, it is difficult to divide the in situ LAI data into a different data set of deciduous and coniferous forest for the LAI modeling. For a SOM-based LAI modeling, a minimum number of the LAI sampling points are needed to train the SOM neural network. Besides the problem of a minimum sampling number for an adequate SOM training process, the successful SOM-based LAI modeling itself does not require a separate training set of deciduous and coniferous forest because the expected LAI of Landsat pixel would be successfully modeled by using the trained SOM neural network that encapsulates the non-linear relationship between in situ LAI data and the spectral reflectance of the corresponding Landsat pixels without the information of forest types of Landsat pixels. The measured in situ LAI value is co-registered to Landsat pixels to analyze a correlation between these two data sets. The co-registered Landsat pixel values are input data set and the in situ LAI values are output data set for the SOM training process. A detailed methodology is explained below.

**Scaling down Remotely sensed LAI modeling:**

The key factor of the scaling down remotely sensed LAI modeling is again the non-linear relationship analysis of Landsat pixel values and MODIS LAI data. In an environmental study, Landsat data is the most widely used satellite image, but it is appropriate for a regional study. The spectral resolution of Landsat data is too coarse to differentiate some critical land cover components. Despite this limitation, Landsat data is still the most widely used data and the oldest data archive among the earth observing satellite sensors. Thus it is better to use Landsat data as a basic satellite data for LAI estimation in a local/regional-scale study. In previous studies, Landsat is the most widely used satellite image for remotely sensed LAI modeling. Although its spatial resolution, 30m², is rather coarse, the pixel of Landsat is closely related to a few tree canopies within pixel boundary, so the site specific LAI estimation is possible. While Landsat has only 7 bands, MODIS provides higher spectral resolution with much coarser spatial resolution. Thus, MODIS data is expected to provide more spectral information of the earth surface by sacrificing much spatial information. By utilizing the higher spectral
information of MODIS, it is expected to model the forest LAI of Landsat image more effectively with MODIS LAI/fPAR than the simple Landsat NDVI. MODIS data provides the detailed spectral resolution (36 bands), while it sacrifices the spatial resolution. Because of its very coarse spatial resolution (≥ 250 m²), MODIS data is an ideal satellite data for a continent/global LAI estimation. The geometrically/radiometrically-corrected MODIS data is used to extract environmental variables of land and ocean using diverse algorithms. For land surface, MODIS provides 8-day LAI/fPAR and Net Primary Vegetation Production (e.g., Net Primary Production and Net photosynthesis). The MODIS land science team produces a global LAI coverage based on three data sets: a surface reflectance data, a land cover classification map, and a cloud state data. Kim and Lee (2004) compared the LAI values of Landsat and MODIS, but did not model MODIS LAI based on Landsat. Due to the coarse spatial resolution and limited archive data of MODIS, it is difficult to expect that MODIS LAI provides detail information of forest activity at regional/local scale, so it is needed to test the utility of a Landsat-LAI modeling based on MODIS LAI data to incorporate the higher spatial resolution of Landsat and the higher spectral resolution of MODIS for a better LAI modeling at regional scale. Landsat LAI modeling based on MODIS LAI data is done by measuring the correlation between MODIS LAI and the co-registered Landsat pixel values. A detailed methodology is explained below.

**Geocomputational Data Mining Method for LAI Modeling:**

Regression analysis has been a popular empirical method of modeling the relationship between spectral data and LAI (Butera 1986; Chen and Cihlar, 1996; Fassnacht et al. 1997; Turner et al. 1999). Although the traditional regression method provides reasonable accuracy in LAI modeling, if it is possible, the LAI modeling of satellite data is better to be analyzed by non-linear, non-parametric analysis methodology. Non-linear relationship can be analyzed by many different methodologies, but it can be effectively analyzed by a geocomputational data mining methodology, specifically Artificial Neural Networks (ANN). ANN has been used intensively in remotely sensed data analysis and has shown a good performance in classification and modeling, often recording overall accuracy improvements in the range of 10-
20 percent. The reasons of the better accuracy of ANN are no prior distribution assumption, accommodation of collateral data such as textural information, slope, aspect and elevation, and flexibility to adapt to improve performance for particular problems. ANN shows a good accuracy in a LAI modeling (Jensen and Binford 2004; Walthalla et al. 2004).

Many studies have modeled LAI based on a classified land cover class data, mainly vegetation types. This approach has a merit in a LAI modeling, but is easily affected by errors from two separate classification and LAI modeling steps. The other LAI modeling approach is to relate in situ LAI value to satellite data and model LAI value of satellite data without creating a classified land cover class data. This one-step approach is to classify a satellite pixel as an appropriate in situ LAI value. This classification based on the measured non-linear relationship is where a geocomputational data mining methodology is required. Among many different methodologies, I propose ANN, specifically Self-Organizing Map neural networks (Kohonen 2001). The backpropagation-multilayered perceptron neural networks have been used most widely, but it has suffered from a local minima problem. As the SOM-based classification is a hard classification, and SOM neural network does not calculate posterior probability, it is difficult to interpolate the expected LAI value according to a posterior probability of Landsat pixel. Thus it is required to employ additional process, a Gaussian Mixture Modeling, for posterior probability calculation (Lee and Lathrop 2006). SOM is based on clustering algorithm, so it can be considered as an enhanced k-means clustering method, a well known data mining methodology. SOM-GMM is expected to provide an accurate LAI modeling of satellite data than conventional statistical methodologies. The utility of SOM-GMM-based LAI modeling will be tested in the future study.

III. Comparing changes of modeled LAI to analyze forest activity change between 1990 and 2002 Landsat Images

The modeled LAI value of Landsat imagery is used to analyze the LAI change of North Korea forest. Because of the archived satellite imagery, it is
possible to model the LAI of Landsat imagery in 1980's and 1990's by using either in situ measurement or MODIS LAI/fPAR data. The modeled LAI values of North Korea forest from 1990 and 2002 Landsat images are expected to show the forest photosynthesis activity in the past and the present. The historical LAI data and changes are very critical information for a local/regional/global carbon circulation modeling and estimating carbon sink in the ecosystem. Biogeochemical models of carbon circulation (e.g., BIOME-BGC) require information of vegetation photosynthesis activity and LAI/fPAR are usually used in these models. Thus the feasibility of the LAI modeling based on the historical Landsat imagery and the current reference data (MODIS LAI/fPAR image and in situ LAI) tested in this study provides valuable information for the carbon sink modeling of North Korea forest.

According to previous studies, temperate forest serves as a carbon sink in a global carbon model, so North Korea forest is also expected to serve as a carbon sink, rather than a carbon source. Although the analysis of a carbon budget of forest ecosystem is not the research objectives of this study, the analysis of LAI change from 1980's to now is expected to show what North Korea forest function is in a global carbon budget. In the case of South Korea forest as shown in Table 1, Korea Forest Service estimated that South Korea temperate forest function as a carbon sink (Ahn, 2005). Thus the future study should estimate accurately the expected carbon sink of CDM-LULUCF activities using biogeochemical models. In terms of that, a biogeochemical model based on LAI data is a useful methodology for this object.

Due to the limitations of this study, the result of this study shows only a partial picture of the historical LAI change of North Korea forest between 1990 and 2002 Landsat images. To increase the accuracy of LAI modeling, more detailed research should be done with more satellite imagery and field measurement. In addition, the future study should focus on applying the estimated LAI value to the biogeochemical model (i.e., BIOME-BGC model) to model the total NPP (Net Primary Production) for the estimation of the total absorbed carbon.
Table 1. Net Greenhouse Gas Emissions / Removals from Land-Use Change and Forestry

<table>
<thead>
<tr>
<th></th>
<th>1990</th>
<th>1995</th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>GR(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>-6,476</td>
<td>-5,793</td>
<td>-9,949</td>
<td>-10,422</td>
<td>-10,156</td>
<td>-9,448</td>
<td>3.5</td>
</tr>
<tr>
<td>1)</td>
<td>-7,155</td>
<td>-6,867</td>
<td>-11,087</td>
<td>-11,552</td>
<td>-11,299</td>
<td>-10,610</td>
<td>3.6</td>
</tr>
<tr>
<td>2)</td>
<td>46</td>
<td>71</td>
<td>82</td>
<td>84</td>
<td>84</td>
<td>88</td>
<td>6.0</td>
</tr>
<tr>
<td>3)</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
<td>-</td>
</tr>
<tr>
<td>4)</td>
<td>633</td>
<td>1,003</td>
<td>1,057</td>
<td>1,046</td>
<td>1,059</td>
<td>1,074</td>
<td>4.9</td>
</tr>
</tbody>
</table>

Note: Negative signs denote removals (or sink); GR represent annual growth rate; 1) changes in Forest and other Woody Biomass Stocks; 2) Forest and Grassland Conversion; 3) Abandonment of Managed Land; 4) CO₂ Emissions and Removals from Soil. Yearbook of Forest Statistics, in various years, (Korea Forest Service). Source Ahn (2005).
Chapter 3. Data and Methods

The study area is not specified by the political boundary, but is the whole Landsat image (Path 117, Row 33) (Figure 1-3). The Landsat image used in this study covers mainly Hwang-Hae-Do and Pyong-An-Nam-Do, and North Korea’s capital, Pyong Yang, which are located in the center of the Landsat image. The Landsat image (Path 117, Row 33) is selected because Hwang-Hae-Do experienced rapid forest destruction from late 1980’s to late 1990’s (MOE 2001) and the symbolic significance of North Korea’s capital, Pyong Yang.

The data used in this study are Landsat TM and ETM images, MODIS LAI/fPAR image, field-sampled LAI, and SRTM (Shuttle Radar Topography Mission) DEM data for topographic correction. The test data set of this study is the Landsat TM taken on August 16th, 1990 and ETM+ taken on September 17th, 2002. These two Landsat images are used to classify forest land cover, measure the forest decrease from 1990 to 2002 and model LAI. In order to do image classification and LAI modeling, the Landsat Level 1G Systematic Corrected Single Scene processed through NLAPS images are required to be preprocessed to remove the effects of atmosphere and topography. The detailed preprocesses of Landsat image is described below.

MODIS LAI/fPAR image and the in situ LAI are the reference data set of the LAI modeling of Landsat image and are acquired in mid-September 2002. MODIS LAI/fPAR image is an 8-day composite data taken on September 2002. The MODIS LAI product is defined as the one-sided green leaf area per unit ground area (Myneni et al. 2002; Privette et al. 2002) and fPAR measures the proportion of available radiation in the photosynthetically active wavelengths (0.4 to 0.7mm) that a canopy absorbs (Myneni et al. 2003). LAI and fPAR are biophysical variables which describe canopy structure and are related to functional process rates of energy and mass exchange. MODIS LAI production algorithm is based on three-dimensional radiative transfer theory which exploits the spectral information content of MODIS surface reflectance at up to 7 spectral bands (Myneni et al. 2002) and is developed for inversion using a look-up-table approach (Knyazikhin et al. 1998a,b; Tien et al. 2004).
When this main algorithm fails, a back-up method using vegetation indices that requires a land cover classification (Knyazikhin et al. 1998a; Myneni et al. 1997) is employed (Myeini et al. 2002). The 1-km MODIS LAI products are generated over an 8-day compositing period (MOD15A2, version4) which is based on the maximum fraction of absorbed Photosynthetically Active Radiation (fPAR) (Myneni et al. 2002). The LAI products are projected on a Sinusoidal 10° grid with 36 × 18 tiles spanning the globe (Myneni et al. 2002) and the images used in this study are reprojected on a UTM to georegister it to Landsat images. The accuracy of MODIS LAI (version 4) for coniferous forest is within 50% (Wang et al. 2004) and within 30% for agricultural area (Tan et al. 2005) from ground base validations.

The methodologies of this study are composed of two parts: image classification and LAI modeling based on Artificial Neural Networks (ANN). Before the actual data analysis, the Landsat satellite imagery should be preprocessed to remove the atmospheric and topographic distortions for an accurate classification and LAI modeling.

I. Preprocessing of Landsat TM/ETM+ images

i. Atmospheric Correction

Vegetation indices (i.e., NDVI) calculated from surface reflectance without atmospheric correction show much worse relationship with the field LAI measurement than the VI from atmospherically corrected imagery (Liang et al. 2001). Thus, it is a critical process to remove atmospheric effects of remotely sensed imagery because the purpose of this study is to estimate LAI value accurately from Landsat satellite imagery.

Atmospheric correction is used to remove the effect of atmospheric scattering from satellite imagery. Compared to the little atmospheric alteration of aerial photograph, the spectral nature of satellite imagery is significantly altered by atmosphere. Multiple sources of variability other than the surface type have effected on the observed spectral response recorded by the satellite sensor. The factors of these variations include atmospheric conditions, the sun angle, the illumination conditions, and the sensor differences. In addition to
the difference of an object’s spectral signature at the ground level as compared to at the satellite sensor, it is also likely to vary temporally from image to image because the atmospheric and climatic changes with time (Miller et al. 1998). To remove the atmospheric effects, it is impossible to apply the complete model to every pixel in a typical remote-sensing image, and independent atmospheric data are almost never available for any given image and certainly not over the full FOV (Field of View) (Schowengerdt 1997).

Atmospheric effects can be summarized as three parameters, transmittance ($\tau$), path radiance ($L_p$) and downwelling irradiance for a specific atmosphere (Berk et al. 1989). These atmospheric parameters are modeled by a radiative transfer model (e.g. 5S or MODTRAN). In atmospheric correction method that relies on a physical modeling of the atmosphere, the sensor DNs are required to be converted into radiances at the sensor, i.e. sensor calibration.

\[ \text{Radiance} = \text{gain} \times \text{DN} + \text{offset} \]

which is also expressed as:

\[ \text{Radiance} = \frac{(L_{\text{MAX}} - L_{\text{MIN}})(Q_{\text{CAL}} - Q_{\text{CALMIN}})}{(Q_{\text{CALMAX}} - Q_{\text{CALMIN}})} + L_{\text{MIN}} \]

where $Q_{\text{CALMIN}} = 1; \ Q_{\text{CALMAX}} = 255; \ Q_{\text{CAL}} = \text{Digital Number of Landsat pixel}; \ L_{\text{MIN}} = \text{Low gain state for each band}; \ \text{and} \ L_{\text{MAX}} = \text{High gain state for each band}$.

The converted radiance values of remotely sensed imagery are then processed to remove atmospheric alteration by using the modeled atmospheric parameters, e.g. path radiance or transmittance for each wavelength. Among many different atmospheric correction models, MODTRAN has been widely used and showed good results in the previous studies, so MODTRAN is used for modeling of atmospheric parameters in this study. Transmittance is simply the percentage of light at a given wavelength that is absorbed by the atmosphere. An appropriate atmospheric transmittance must be calculated for each spectral band of the satellite sensor to restore the missing data that has been absorbed by the atmosphere. This is done by convolving each band’s spectral response function with the atmospheric transmittance as a weighted average transmittance value for each band’s range of wavelength.
ii. Topographic correction

As the study area is a typical mountainous landscape, topographic correction is at least as important as atmospheric correction. Topographic shading modifies surface reflectance and affects the inversion of land surface parameters. Topographic correction requires accurate digital elevation model (DEM) data. Until the Shuttle Radar Topographic Mission (SRTM) (Figure 4–6) DEM is available, it is difficult to do topographic correction in a landscape where conventional DEM is not available. Although the available SRTM DEM of North Korea is rather coarse, 3 arc second that is about 90m spatial resolution, than the original SRTM DEM data with 1 arc second that is about 30m² spatial resolution, SRTM global DEM data provides enough spatial resolution for topographic correction of Landsat imagery. I use the modified Sun-Canopy-Sensor Correction (Gu and Gillespie 1998) model, SCS+C Correction model (Soenen et al. 2005).

The SCS+C model is proposed to overcome the overcorrection problem of SCS model, similar to that with the cosine correction. As the angle of incident approaches 90°, the correction factor becomes excessively large. In the C-correction (Teillet et al. 1982), the parameter C has been shown to have a moderating influence on the cosine correction by emulating the effect of diffuse sky illuminations (Teillet et al. 1982).

The SCS+C model integrates the moderator C of the C-correction model within the improved physical context of the SCS model. This addition is intended to be an improvement to the SCS correction in a similar way as the C-correction improves on the cosine correction. The formulation of the SCS+C correction is

\[ Ln = L \left( \frac{\cos \alpha \cos \theta + C}{\cos i + C} \right) \]

where \( \alpha \) is the terrain slope, \( \theta \) is the solar zenith angle, \( i \) is the incident angle, and \( C \) is the semi-empirical moderator to the cosine correction. The parameter \( C \) is estimated based on an examination of image data, a linear relationship between \( L \) and \( \cos i \) in the form:
\[ L = a + b \cos i \]

where \( L \) is the uncorrected reflectance. The parameter \( C \) is a function of the regression slope \( (b) \) and intercept \( (a) \)

\[ C = \frac{a}{b} \]

For more information for C-correction, refer to Teillet et al. (1982).

**Figure 1.** Landsat TM image (Path 117, Row 33) acquired on August 16\(^{th}\), 1990 shown in false-color composite (Red: Band 4, Green: Band 5, and Blue: Band 3)
Figure 2. Landsat ETM+ image (Path 117, Row 33) acquired on September 17\textsuperscript{th}, 2002 shown in false-color composite (Red: Band 4, Green: Band 5, and Blue: Band 3)

Figure 3. The significantly deforested area of North Korea shown in false-color composite (Red: Band 4, Green: Band 5, and Blue: Band 3)
Figure 4. SRTM DEM image of the study area with 90m spatial resolution

Figure 5. SRTM Slope image of the study area derived from DEM data 90m spatial resolution
Figure 6. SRTM Aspect image of the study area derived from DEM data with 90m spatial resolution

II. Land Use Classification and LAI Modeling of Landsat TM/ETM+ images

i. Maximum-Likelihood Hard Classification

The atmospheric/topographic corrected Landsat images are classified to the simplified land cover/land use classes. The purpose of the classification of the Landsat image is not to create a detailed LU/LC map, but to analyze the land cover change from forest to other land cover classes. Therefore, it is enough to use simplified land cover classes: urban (bare soil), crop land, shrub/forest, and water. Due to the limited spectral resolution of Landsat sensor, it is extremely difficult to differentiate bare soil from concrete/asphalt-covered urban landscape and the differentiation of bare soil and concrete/asphalt is not required in this study.
By using these simplified land cover classes, it is possible to attain relatively high accuracy of a land cover map. Maximum-likelihood hard classification method is used to classify the preprocessed Landsat imagery. The other more advanced classification algorithms (i.e., Artificial Neural Network) can be used to attain higher classification accuracy. But these advanced classification algorithms are difficult to implement because the classification accuracy is greatly affected by the input parameter values of the algorithm and then it is difficult to find the best combination of the input parameter values. Due to these difficulties of the other advanced classification algorithms and the simplified land cover classes, it is enough to use Maximum-Likelihood Hard Classification algorithm to analyze the land cover change of North Korea forest.

The training pixels of maximum-likelihood classification are collected from a large homogeneous area vividly identified in Landsat image. The selected training pixels are further examined in the feature space to exclude the outlier training pixels. Then, the classified Landsat image is verified against the late 1980's land cover map for a correct classification. To get the most accurate classification, several different training sets are tested and then the most accurately classified LU/LC map is selected. As the purpose of this study is to model forest LAI, minor misclassification of non-forest land cover classes are not further refined and all non-forest land cover classes are merged as non-forest class. Thus the final land cover map has only two classes: forest and non-forest. The final land cover map is used to mask out the test pixels of Landsat image for LAI modeling.

ii. Three Different Leaf Area Index Modeling Algorithms

Leaf Area Index is usually measured in field, not directly extracted from satellite imagery like vegetation indices. A modeling approach should be used to estimate LAI value from satellite imagery. This study tests three different methodologies to model the Leaf Area Index (LAI) of Landsat imagery based on in situ measurement, Vegetation Indices (VI), and MODIS LAI/fPAR. While VI-based LAI modeling is the simplest and straightforward method because it is based on a linear equation of the previous study, the estimated LAI of the other two methodologies are modeled by using SOM (Self-Organizing Map)-LVQ (Learning Vector Quantization) neural networks.
a. The VI-based LAI modeling

It is based on the relationship between vegetation indices and in situ LAI. Many studies have tried to build a VI-based simple equation to retrieve LAI by using vegetation indices like NDVI. As this method is based on a field measured LAI, VI-based LAI modeling is very similar to the other ANN-based LAI modeling algorithm which is also based on field measured LAI. Although this method is simple and easy to use, it is difficult to expect high accuracy of LAI modeling in this study because the equation is modeled based on in situ LAI not measured in the study area. Despite of its limitations, I have used this method to test whether all three LAI modeling methodologies show a consistent result in LAI change analysis. The previous studies modeled simple linear or nonlinear equations of crop/tree LAI, but it is difficult to find Landsat VI-based LAI model equation of tree LAI. It is partly because of the complex relationship between Landsat vegetation indices and in situ LAI to be modeled in simple linear/non-linear equation. To avoid this problem, I use WDVI (Weighted Difference Vegetation Index, Clevers 1989), not modeled LAI based on vegetation indices. According to Fang and Liang (2003), WDVI calculated from atmospherically corrected surface reflectance shows much stronger linear relationship with in situ LAI than NDVI (Figure 9). In addition, both NDVI and WDVI from Top-Of-Atmosphere radiance show much worse relationship with LAI (Figure 7). Thus it is possible to assume that WDVI is linearly related to LAI, so LAI change can be tested by comparing the WDVI images of 1990 and 2002 Landsat calculated from surface reflectance. Although there will be large uncertainties in predicting LAI based on the VI-related statistical relationships, the strong linear relationship of WDVI and LAI is good enough to analyze the LAI change at regional scale, not at pixel-level scale. The WDVI used in this study is calculated from the atmospherically and topographically corrected Landsat radiance. Once the Landsat radiance is converted to surface reflectance, WDVI is calculated by the following equation:

$$WDVI = \rho_n - \gamma \rho_r$$

where $\gamma$ is the slope of the soil line, $\rho_n$ is reflectance in Red band; $\rho_r$ is reflectance in Near-Infrared band; $\gamma$ value is the slope of the soil line that is
1.05 (Liang 2004);

**b. In Situ field-measured LAI-based Modeling**

This algorithm measures the non-linear relationship between *in situ* LAI and the pixel value of Landsat image by using SOM-LVQ neural networks. Unlike traditional parametric statistical classification methods, SOM-LVQ neural networks, a semi-parametric statistical method, is expected to measure the non-linear relationship more accurately. The training of SOM-LVQ NN is done by using *in situ* LAI data as an output data and the co-registered Landsat pixel value as an input data. The *in situ* measured LAI data was collected at Kwang-Neung Forest in August and September, 2002 (Hwang, in preparation) (Figure 10). As the *in situ* LAI was collected in Kwang-Neung Forest of South Korea, the corresponding Landsat image (Path 116, Row 34) is purchased that is acquired on September 10th, 2002. This Landsat image is also atmospherically and topographically corrected by using MODTRAN and SCS+C algorithm with 30m DEM data. As 30m DEM data is used for Landsat image to correct topographical distortion as compared to 90m SRTM DEM data for the Landsat images of North Korea, it is expected that the Landsat image of Kwang-Neung Forest is much more accurately corrected for topographic distortion. Due to the limited field measurements, this study does not discriminate the forest types (Deciduous vs. coniferous), but use all field measured LAI value as one data set. It is expected that SOM-LVQ NN captures effectively the non-linear relationship between *in situ* LAI and Landsat pixel value without any information of forest type. Once SOM-LVQ NN is trained by using *in situ* LAI, the individual pixel values of Landsat image of 1990 and 2002 (Path 117, Row 33) are applied to the trained SOM-LVQ NN and then each pixel is labeled as the best-matching unit label of the SOM-LVQ NN.

**c. MODID LAI/fPAR-based Modeling**

The MODIS LAI/fPAR-based modeling is done by the same method of *in situ* LAI modeling. The only difference is that this model uses MODIS LAI/fPAR data created on September 14th, 2002 as a reference data, so there would be little seasonal difference between MODIS and Landsat acquired on September 17th, 2002. As MODIS data is on Integerized Sinusoidal, the MODIS
LAI/fPAR image should be reprojected to UTM to register it to Landsat imagery (Figure 11). But it is not easy to generate the training set for SOM-LVQ NN because the spatial resolution of MODIS LAI/fPAR data is 1km². There would be more than 900 Landsat pixels for each MODIS pixel and it is difficult to expect that the selected Landsat pixels for each MODIS pixel are accurately registered and correspond well to MODIS LAI value. Thus it is expected that the trained SOM neural network based on over 900 Landsat pixels for each MODIS LAI value is significantly affected by the high spatial heterogeneity of Landsat pixels and the image registration problem between MODIS and Landsat due to the significant difference of spatial resolution. The image registration problem significantly decreases the accuracy of LAI modeling by introducing non-forest Landsat pixels and MODIS pixels of which land cover is not entirely forest in the SOM training process. To minimize these problems of image registration and spatial heterogeneity in generating the training set of SOM NN, the pixels of MODIS LAI/fPAR are selected on a large homogeneous forest area of a preclassified land cover map and the co-registered Landsat pixels for each MODIS pixel are selected from the very inner region of MODIS pixel. The selected MODIS pixels from a large homogeneous forest cover are converted to polygon coverage and then the polygons are inner-buffered 200m from the pixel boundary (Figure 12). The core area of the inner-buffered polygon is 600m², so the selected Landsat pixels for each MODIS pixel are 400. As a result, it is expected that the selected Landsat pixels are well correspond to MODIS LAI value. Unlike the previous method based on a very limited number of field measurements, this MODIS-based LAI modeling is based on a large number of Landsat and MODIS pixels to model the non-linear relationship between Landsat and MODIS LAI, so this method is expected to have little effect from extreme condition. Once the SOM-LVQ NN is trained based on the training set of Landsat image acquired on September 17th, 2002, the rest test pixels of Landsat image acquired on 2002 and the test pixels of Landsat image acquired on 1990 are classified to label the appropriate LAI value for each test pixel based on the trained SOM-LVQ NN.

iii. Analysis of forest LAI change between 1990 and 2002
The three differently modeled LAI outputs of 1990 and 2002 Landsat images are compared to test whether there is any change in the photosynthetic activity of North Korea forest between 1990 and 2002. The main purpose of this analysis is to test whether all three algorithms show consistent changes between 1990 and 2002 Landsat images. As the three differently modeled LAI outputs of 1990 and 2002 Landsat images are based on different theoretical background and reference data set, it is difficult to expect that all three algorithms show consistent results with no exception. If all three algorithms show consistent results, the feasibility of modeling the past LAI of Landsat image by using the present MODIS LAI/fPAR data or in situ LAI data is proved.

The changes of the modeled LAI outputs of 1990 and 2002 are analyzed by using the total sum of LAI values of Landsat pixels, the statistical parameters of the modeled LAI results, and image comparison. The total sum values and statistical parameters are summarized in tables and the color-coded LAI images are included for visual comparison. The typical pixel-to-pixel comparison is not a good way to compare the results because of the significant pixel-to-pixel variations according to high spatial heterogeneity of Landsat image.

![Graphs showing the relationship between ground measured LAI and VI calculated from TOA radiance of various vegetation indices.](image-url)

Figure 7. Ground measured LAI vs. VI calculated from TOA radiance of
Landsat ETM⁺ (Liang 2004)

Figure 8. Ground measured LAI vs. VI calculated from TOA reflectance of Landsat ETM⁺ converted from TOA radiance (Liang 2004)

Figure 9. Ground measured LAI vs. VI calculated from surface reflectance of Landsat ETM⁺ that is calculated from atmospheric correction of
TOA radiance (Liang 2004)

Figure 10. Sampling Points of *In Situ* Field-Measured LAI on Landsat ETM+ Image shown in false-color composite (Red: Band 4, Green: Band 5, and Blue: Band 3)

11.1 MODIS LAI/fPAR Image on Integerized Sinusoidal Projection

11.2 Reprojected MODIS LAI/fPAR Image on UTM Projection

11.3 Enlarged MODIS LAI/fPAR Image

Figure 11. Reprojection of MODIS LAI/FPAR from Integerized Sinusoidal
Figure 12. The Pixel Boundary and Core Area of MODIS Pixel to select Landsat training pixels for the LAI Modeling between Landsat and MODIS LAI/fPAR. The buffer distance from MODIS Pixel Boundary is 200m.
Chapter 4. Results

The results of this study, the classified forest cover map and the LAI modeling outputs of 1990 and 2002 Landsat images, are shown in color-coded images, histograms, and tables. The forest cover of the study area, a Landsat Path 117, Row 33 image, have been reduced between 1990 and 2002 and the modeled LAI values of 2002 Landsat are lower than that of 1990 Landsat.

The Landsat classified land cover maps of 1990 and 2002 are shown as one overlapped image (Figure 13). The overlapped forest covers of 1990 and 2002 Landsat images show significant forest reduction in the study area. The forest area of 1990 Landsat image is estimated as 540278ha, 17.6% of the entire Landsat image, but the forest area of 2002 Landsat image is estimated as 508195ha, 16.6% of the entire Landsat image (Table 2). Forest cover about 1% of the forest cover of 1990 Landsat image, 32083 ha, have been converted into other land cover type. The overlapped image of 1990 forest (red color) and 2002 forest (black color) clearly shows the forest reduction in the study area of North Korea (Figure 13). There is no significantly large forest clearcut, but there is gradual forest destruction along the forest edge. The many speckled red dots of the classified forest cover map of 1990 Landsat may represent the classification error of 1990 Landsat as these dots are relatively small to be considered as a forest stand.

The results of 1990 and 2002 WDVI images calculated from surface reflectance of 1990 and 2002 Landsat images are shown in Table 3 and Figure 14 and 15. The comparison of the two WDVI images clearly shows the decline of WDVI value between 1990 and 2002. The WDVI images of 1990 Landsat (Figure 14) and 2002 Landsat (Figure 15) show clear difference of coloration between two years. Although two WDVI images are color-labeled in 10 classes, there are two classes with no pixels in 1990 WDVI and three classes with no pixels in 2002 WDVI because the max WDVI value of two images are less than 0.7 and 0.8, respectively (Table 3). The enlarged result image of 2002 WDVI have less pixels colored as cyan than that of 1990 WDVI. The WDVI decline from 1990 to 2002 is also confirmed by the statistical parameters and histograms (Table 3 and Figure 16). All statistical parameters except Min value
are larger in 1990 WDVI than in 2002 WDVI, especially in Mean (0.362 and 0.323, respectively) and Median (0.355 and 0.312, respectively). These differences of the statistical parameters are clearly shown in the histograms of both WDVI images. The histogram of 1990 WDVI shows clear dual-mode distribution, while the histogram of 2002 WDVI shows left-shifted single-mode distribution. Based on this result and the previous study (Liang 2004), it can be deduced that the forest LAI of the study area have reduced between 1990 and 2002 Landsat images.

The other two LAI modeling are done by SOM-LVQ NN. Unlike previous indirect LAI modeling methodology based on strongly linear-correlated WDVI, the other two methodologies utilize SOM-LVQ NN to model LAI value of Landsat pixel directly from reference LAI data. In SOM-based LAI modeling, while many parameters of SOM-LVQ NN should be chosen very carefully, the crucial step is to define the structure of SOM-LVQ NN. As a two dimensional SOM-LVQ NN is used in this study, the x-/y-dimensions of the codebook vector map of SOM-LVQ NN are the most important parameters of SOM-LVQ NN. After several tests of SOM neural networks with different x-and y-dimensional numbers, the most accurate SOM NN model is selected and used to model the LAI of the test pixels of 1990 and 2002 Landsat images. The selected structures of SOM-LVQ NN are the 18 x-dimension and 15 y-dimension network for MODIS-based LAI modeling (Figure 17) and 10 x-dimension and 8 y-dimension network for in situ LAI-based modeling (Figure 21). Figure 17 and 21 are the images of the actual two-dimensional SOM-LVQ NN with the assigned LAI value for each node.

The MODIS-based SOM modeling results are shown in Figures 18–20 and Tables 4 and 5. First of all, the color-coded output images of the MODIS-modeled LAI of 1990 and 2002 Landsat images clearly show the difference of the modeled LAI between two years. The output LAI image of 1990 Landsat shows more blue coloration as compared to that of 2002 Landsat. It means that, likewise the WDVI results, the MODIS-based LAI modeling of 1990 and 2002 image show the decline of LAI value in 2002 Landsat image as compared to 1990 Landsat image. In addition, the output image of 2002 Landsat shows more speckles than that of 1990 Landsat. The suspected reason of this speckled pattern in the output image of 2002 Landsat is further discussed in the next chapter. The coloration difference of the output LAI images are
confirmed by total sum (Table 4), statistical parameters (Table 5), and histogram (Figure 20).

As the MODIS LAI/fPAR data is in unsigned 8-bit format with a valid range of 1 and 100, the classified LAI results of 1990 and 2002 Landsat images are also in unsigned 8-bit format. Although the histogram and statistical parameters are shown in unsigned 8-bit format to show the original data distribution and its statistical properties, the comparison of the total sums of the modeled LAI of 1990 and 2002 Landsat based on MODIS LAI (Table 4) is not based on the original data value, but the modeled LAI value is multiplied by scale factor, 0.1, to convert it to the actual LAI value. But the histogram of the output LAI image is constructed in the original 8-bit data format to show the LAI distribution in the original MODIS LAI value.

The total sum values of MODIS-based modeled LAI of 1990 and 2002 Landsat are about 3669108 and 2942523, respectively. This result also confirms the visual comparison of the output LAI images. The estimated LAI of 1990 Landsat is significantly higher than that of 2002 Landsat in most pixels. This conclusion is verified again by the statistical parameters of the output LAI images (Table 5 and Figure 20). Unlike WDMI, the MODIS-based LAI modeling shows the same MIN and MAX value in both Landsat images because, while WDMI is calculated directly from surface reflectance value, the MODIS-based LAI modeling is done by the trained SOM-LVQ NN in which all nodes are labeled by MODIS LAI values with a range of 31 and 61. All three parameters, mean, median and mode, are higher in the output LAI image of 1990 Landsat than that of 2002 Landsat, especially in mean (55.199 and 50.364, respectively) and median (57 and 47, respectively). These differences of the output LAI images of 1990 and 2002 Landsat images in three parameters are clearly shown in the histograms (Figure 20). The histogram of the modeled LAI of 1990 Landsat shows a narrow range between Mean (55.19) and Max (61) with more pixels above Mean, while that of 2002 Landsat shows a wider range between Mean (50.36) and Max (61) with more pixels below Mean. Based on these results, I conclude that the modeled LAI of 1990 Landsat in most pixels are estimated higher than that of 2002 Landsat.

The second SOM-LVQ NN modeled LAI results are based on in situ field-measured LAI at Kwang-Neung Forest. The output images of field-measure
LAI modeling are classified into 9 classes with same class increment, 0.5. As the maximum value of the *in situ* LAI is 4.51, the pixels classified as 4.51 are color-coded as a class with a range of 4.0 and 4.5. Again, the LAI modeling output of 1990 and 2002 Landsat images based on *in situ* LAI show a consistent result with the previous two methodologies: higher LAI values in most pixels of 1990 Landsat image than that of 2002 Landsat image. Likewise the MODIS-based LAI modeling, the output image of *In Situ* field-measured LAI modeling of 1990 Landsat (Figure 22) show much more blue coloration than that of 2002 Landsat (Figure 23). The enlarged images of the sub-study area (Figure 22.2 and 23.2) show the coloration difference more clearly. The modeled LAI of 2002 Landsat shows a clear topographical pattern in the output image, while that of 1990 Landsat shows little topographical pattern, but a problem of maxed-out blue coloration.

The total sum of the *in situ* LAI modeling results of 1990 and 2002 images are about 14919411 and 13573199, respectively (Table 6). As the modeling output is based on a few specific LAI values, it is difficult to know how the modeling outputs are different in a specific LAI value without the comparisons of statistical parameters (Table 7) and histograms (Figure 24). While the mode value of 2002 Landsat is higher than that of 1990 Landsat, the other two parameters, Mean and Median, are higher in the output image of 1990 Landsat (3.207 and 3.485) than that of 2002 Landsat (2.999 and 2.812). As the output images of 1990 and 2002 Landsat images show different results in median and mean, we know that more pixels are estimated to have higher LAI value than mean value in 1990 Landsat, but the composite result in the output image of 2002 Landsat. The histograms of both *in situ* LAI-modeling outputs clearly show the difference: more pixels of 1990 Landsat and less pixels of 2002 Landsat are located on the right side of mean (Figure 24.1 and 24.2).
Table 2. The Classified Forest Land Cover Area of 1990 and 2002 Landsat Images

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>540278 ha (17.6%)</td>
<td>508195 ha (16.6%)</td>
</tr>
<tr>
<td>Forest Destruction</td>
<td>32083 ha (5.94% of 1990 Forest Cover)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 13. Classified Forest Land Cover Map of 1990 and 2002 Landsat Images where 1990 Forest Area is colored in Red and 2002 Forest Area is colored in Black
Figure 14. WDVI calculated from the surface reflectance of 1990 Landsat image

Figure 15. WDVI calculated from the surface reflectance of 2002 Landsat image
Table 3. Statistical Parameters of the WDVI of 1990 and 2002 Landsat Images calculated from Surface Reflectance

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>0.00998</td>
<td>0.05074</td>
</tr>
<tr>
<td>Max</td>
<td>0.76553</td>
<td>0.67632</td>
</tr>
<tr>
<td>Mean</td>
<td>0.36200</td>
<td>0.32300</td>
</tr>
<tr>
<td>Median</td>
<td>0.35529</td>
<td>0.31221</td>
</tr>
<tr>
<td>Mode</td>
<td>0.39661</td>
<td>0.30244</td>
</tr>
</tbody>
</table>

16.1 Histogram of WDVI Image of 1990 Landsat

16.2 Histogram of WDVI Image of 2002 Landsat

Figure 16. Histograms of WDVI Images calculated from surface reflectance of 1990 and 2002 Landsat Images
Note: The SOM labels are the LAI value of MODIS LAI/fPAR image.

Figure 17. The trained SOM-LVQ Neural Network (15x18 two dimensional structure) based on the Landsat input data and the MODIS-LAI reference data.

Table 4. Total Sum of the MODIS-LAI Modeling Outputs of 1990 and 2002 Landsat Images

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Sum of LAI</td>
<td>36691086</td>
<td>29425228</td>
</tr>
<tr>
<td>Total Landsat Pixels</td>
<td></td>
<td>4564733</td>
</tr>
</tbody>
</table>
Figure 18. MODIS LAI Modeling Output of 1990 Landsat image

Figure 19. MODIS LAI Modeling Output of 2002 Landsat image
Table 5. Statistical Parameters of the MODIS-LAI Modeling Outputs of 1990 and 2002 Landsat Images

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>Max</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>Mean</td>
<td>55.199</td>
<td>50.364</td>
</tr>
<tr>
<td>Median</td>
<td>57</td>
<td>47</td>
</tr>
<tr>
<td>Mode</td>
<td>57</td>
<td>47</td>
</tr>
</tbody>
</table>

20.1 Histogram of the Modeled LAI of 1990 Landsat

20.2 Histogram of the Modeled LAI of 2002 Landsat

Figure 20. Histograms of MODIS LAI Modeling Outputs of 1990 and 2002 Landsat Images
Figure 21. The trained SOM-LVQ Neural Network (8x10 two dimensional structure) based on the Landsat input data and the in situ LAI reference data. The SOM labels are the in situ LAI values.

Table 6. Total Sum of the in situ LAI Modeling Outputs of 1990 and 2002 Landsat Images

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Sum of LAI</td>
<td>14919411</td>
<td>13573199</td>
</tr>
<tr>
<td>Total Landsat Pixels</td>
<td></td>
<td>4564733</td>
</tr>
</tbody>
</table>
Figure 22. *in situ* LAI Modeling Output of 1990 Landsat image

Figure 23. *in situ* LAI Modeling Output of 2002 Landsat image
Table 7. Statistical Parameters of the \textit{in situ} LAI Modeling Outputs of 1990 and 2002 Landsat Images

<table>
<thead>
<tr>
<th></th>
<th>1990 Landsat</th>
<th>2002 Landsat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>1.860</td>
<td>1.860</td>
</tr>
<tr>
<td>Max</td>
<td>4.510</td>
<td>4.510</td>
</tr>
<tr>
<td>Mean</td>
<td>3.207</td>
<td>2.999</td>
</tr>
<tr>
<td>Median</td>
<td>3.485</td>
<td>2.812</td>
</tr>
<tr>
<td>Mode</td>
<td>2.460</td>
<td>3.920</td>
</tr>
</tbody>
</table>

24.1 Histogram of the Modeled LAI of 1990 Landsat

24.2 Histogram of the Modeled LAI of 2002 Landsat

Figure 24. Histograms of \textit{in situ} LAI Modeling Outputs of 1990 and 2002 Landsat Images
Chapter 5. Discussion

The main objective of this study is to model the LAI value based on the different algorithms (WDVI and SOM-based geocomputation) and reference data (MODIS and \textit{in situ} LAI) to test the feasibility of the LAI change analysis for monitoring the future CDM Afforestation/Reforestation project of North Korea. As the results of the three different methodologies show consistent results, this study suggests that it is feasible to use the tested methodologies, especially SOM-based geocomputational LAI modeling method, to monitor the carbon storage of CDM A/R project by analyzing LAI change based on the historical satellite images and the present reference data. As many remote sensing methodologies are suggested for monitoring CDM A/R project of the Kyoto Protocol, this study is verified again the applicability of remote sensing technique for the monitoring of carbon storage as a consequence of CDM A/R project.

To model the LAI of Landsat image accurately, the Landsat images of 1990 and 2002 are thoroughly processed to remove the atmospheric and topographic effects on the spectral property of Landsat imagery. The methodologies used in this study (MODTRAN and SCS+C) are most widely used and the accuracies of these methodologies are verified in previous studies. As Fang and Liang (2003) pointed out, it is extremely important to remove the atmospheric and topographic effects from Landsat image to model LAI correctly based on vegetation indices. Due to the limited access of climate and topographic data of North Korea, the atmospheric and topographic correction processes used in this study are expected to have a limited accuracy, but, once these information are available, more accurate atmospheric and topographical corrections are possible and then the accuracy of the LAI modeling would be enhanced greatly. Although the SRTM DEM “Finished” 3 Arc Second (\textasciitilde 90m) data used in this study for topographic correction is with limited spatial resolution, it might be impossible to do topographic correction without SRTM data in a place like North Korea where the topographic data is very limited and restricted to the public. Thus the results of this study suggest that, as the usefulness of the LAI modeling methodologies tested in this study is verified,
the LAI modeling accuracy can be improved greatly by using more accurate climate data to MODTRAN-based atmospheric correction and high spatial resolution elevation data to SCS+C topographic correction. As the topographic correction of the Landsat image where the in situ LAI taken is processed based on the 30m DEM data, the topographic distortion of the Landsat pixels corresponding to the in situ LAI are expected to be corrected more accurately than that of North Korea. Despite of the successful implementation of atmospheric and topographic correction in this study, it is still required to pursue the better and fully-accounted algorithms for atmospheric and topographic correction with a complete on-time climate data and an elevation data with sufficient spatial resolution.

The classified forest cover maps of the atmospherically / topographically-corrected 1990 and 2002 Landsat images show clearly the reduced forest cover in 2002 as compared to 1990 (Figure 13). As the destructed forest area is too large to be considered as a classification error, there is no doubt that the forest cover in the Landsat image (Path 117/Row 33) is decreased from 1990 to 2002, but there would be a certain degree of a classification error. Although many different Maximum-Likelihood Classification models are tested and the best result is used, the uncertainty of the classified forest cover map is still high in some situations to be used with 100% assurance. In addition, the classification process is done with only the spectral information of Landsat image with no ancillary data set, so the classified forest cover maps of 1990 and 2002 Landsat images are accurate enough to test the forest land cover change at a regional scale, but are still needed to enhance the classification accuracy with additional ancillary data. Thus it should be warned that the result of the forest cover change shown in this study should not be used as an absolute value as a reference data.

With the atmospherically and topographically corrected Landsat images, the LAI modeling of Landsat image is carried out by using the three different algorithms. Although the first methodology, WDVI of Landsat image as a substitute of LAI estimation, do not directly estimate LAI from Landsat image, the comparison of WDVI images of 1990 and 2002 Landsat show a consistent result with the results of the other two methodologies. According to Fang and Liang (2003), WDVI calculated from surface reflectance of Landsat image shows a strong linear relationship with the in situ LAI. Thus there would be a
high uncertainty to use the WDVI to predict actual LAI value at a pixel level, but the comparison of WDVI images provides enough accuracy to analyze the LAI change between 1990 and 2002 Landsat images at a regional scale. It is important to remind that the purpose of WDVI analysis is not to predict LAI value itself, but to infer a general trend of the LAI change between 1990 and 2002 Landsat image at regional scale and test the consistency of the WDVI result with the other two direct LAI modeling results. If the relationship between WDVI and LAI is further modeled and verified with more comprehensive in situ LAI data and sophisticated analysis methodologies, it would be possible to use WDVI as a substitute of the field measurement of LAI to predict LAI value at a pixel level, but it would require intensive field work and thorough verification.

While the WDVI comparison is not a direct modeling process based on LAI reference data, the other two methodologies based on MODIS- and in situ LAI reference data set and geocomputational algorithm (SOM-LVQ NN) are more straightforward LAI modeling process than the WDVI comparison. As mentioned above, the utilities of all three methodologies are verified at least for testing a general LAI change on a regional scale. Unlike other artificial neural networks, such as Multilayer Perceptron neural network, SOM-LVQ NN used in this study is a two dimensional network structure and powerful tool to analyze complex non-linear relationship. The results of this study confirm again the utility of SOM-LVQ NN in the analysis of a complex data set, such as remotely sensed image with dual mode non-Poisson distribution. The significant finding of this study is that the SOM-LVQ NN trained by using MODIS/in situ LAI reference data provides enough accuracy for modeling LAI value at a regional scale. While the output image of the in situ LAI modeling of 1990 Landsat (Figure 22.2) shows little topographic pattern, the other output images of both SOM-based LAI modeling show clear topographic pattern. It means that, although the topographic effect is removed via SCS+C topographic correction process, the forest type would be different along the locations with different aspects and the trained SOM-LVQ NN differentiates the pixels with different aspect successfully and then estimates LAI value according to the detected difference. Despite of the simple implementation and classification power, the best combination of the parameters of SOM-LVQ NN is difficult to configure, so many SOM-LVQ
neural networks with different structure and parameters were constructed and evaluated to find the most optimized SOM-LVQ NN for the LAI modeling. One finding is that the output image of the LAI modeling based on too large (larger than 20 x-/y-dimension) or small (smaller than 10 x-/y-dimension) two-dimensional structures of SOM-LVQ NN tends to have more speckles which may represent false classification. Further study must be followed for a practical application of the evaluated methodologies, but this study shows the applicability of the SOM-based geocomputational LAI modeling for a carbon storage analysis at a regional scale.

The output images of MODIS-based LAI modeling of 1990 and 2002 Landsat images show an additional difference besides the LAI change. While the MODIS-modeling output image of 1990 Landsat shows clear topographic pattern with little speckles, that of 2002 Landsat shows less clear topographic pattern with more speckles. This kind of difference is not expected because the MODIS-based LAI modeling is based on the MODIS and Landsat images taken at the same time, mid-September 2002. It is too early to tell the reason, but the suspected reason is that the seasonal effect on the spatial heterogeneity of 2002 Landsat is higher than that of 1990 Landsat. As 2002 Landsat is taken on mid-September, some trees are started to wither depending on species and topographic location and then the withered trees are resulted in higher spatial heterogeneity of 2002 Landsat image. But, as the in situ LAI modeling of 2002 Landsat shows little problem of speckles, the high spatial heterogeneity of 2002 Landsat due to the withered tree might be not the reason, even if it is not completely off the table. The other suspected reason is the LAI modeling process of the trained SOM-LVQ NN. Compared to the in situ LAI modeling, the MODIS-based LAI modeling uses much more training pixels which may introduce significantly high spatial heterogeneity in the training process as compared to the in situ LAI modeling with limited sampling data. Thus the trained SOM-LVQ NN of the MODIS-based LAI modeling may be over-trained to account the high spatial heterogeneity of 2002 Landsat, while that of the in situ LAI modeling may have little overtraining problem. Further study is needed to clarify the speckle problem in the MODIS-based LAI modeling of 2002 Landsat.

While the output images of MODIS-based LAI modeling show a speckle problem, the output images of the in situ LAI modeling show little problem of
speckles, but show another problem, maxing out in most forest pixels (Figure 22). As compared to that of MODIS-based modeling (Figure 18), the output image of the in situ LAI modeling of 1990 Landsat shows too much blue coloration with little topographic pattern (Figure 22). With the limited reference data, it is difficult to tell whether the maxing out problem of the in situ LAI modeling of 1990 Landsat is caused by the limited training set of the in situ LAI or whether most pixels of 1990 Landsat actually have the spectral reflectance properties of the training pixels which are labeled as the upper two LAI classes. This maxing out problem should be further tested with sufficient in situ field-measured LAI reference data set. Despite of these minor differences, the utility of SOM-LVQ based LAI modeling is proved in this study.

As the results of this study show a consistency in the LAI modeling outputs of 1990 and 2002 Landsat images, the main research objective is achieved, but, at the same time, this study is suffered from a serious problem of the limited data availability. Besides the ground-measured reference data, there are limited Landsat images with little cloud coverage due to the 16-day repeat cycle of Landsat satellite. In 1990, the Landsat scene taken on August 16th is the most timely-matched leaf-on cloud-free image to the in situ LAI data. Although there is almost one month gap between 1990 and 2002 Landsat images, there is no alternative to use.

But, if this problem is looked at from different point-of-view, the problem of the timely-not-matched Landsat images provides additional insight on the LAI change analysis. As the purpose of LAI change analysis is to model how much carbon is up-taken by the forest, the carbon cycle modeling requires year-long data on LAI change along the tree growth. If the two Landsat images are considered as Landsat images taken in the same year, the results of this study clearly verify the possibility of the LAI modeling algorithm for the carbon cycle modeling with the year-long Landsat images and ground-measured LAI reference data set. Thus it is expected that more accurate LAI change analysis is possible with more Landsat images and reference data because the LAI change between 1990 and 2002 Landsat images is analyzed successfully with just a single LAI reference data.

The most important finding of this study is the possibility of LAI modeling of the past Landsat image based on the present MODIS LAI image and in situ
LAI data. The decreasing LAI between 1990 and 2002 Landsat seems obviously granted because of the seasonal difference, but we are not sure this seemingly granted result unless it is empirically proved because the reference data was taken on mid-September 2002. Specifically, the MODIS-based LAI modeling is expected to be problematic because of the significantly coarse spatial resolution of MODIS satellite sensor. It is naturally expected that the MODIS-based LAI modeling would have little utility because of the high uncertainties of MODIS-based LAI modeling. The consistent result of the MODIS-based LAI modeling proves the possibility of LAI modeling of the past Landsat image based on current MODIS data. Despite of the limited accuracy of MODIS LAI/fPAR image, the availability of MODIS LAI image and the applicability of MODIS-based LAI modeling as proved in this study provide a valuable opportunity to study the historical LAI change on a place like North Korea where it is extremely difficult to model the historical LAI change because of the exceptionally restricted accessibility and the little availability of ancillary and reference data set.

The result of this study is expected to be used to scaling-up LAI modeling from local to regional and then a continental scale. A large scale modeling usually have a large degree of uncertainty because of the coarse resolution of the source data, but the above regional-scale LAI modeling of Landsat imagery minimizes the uncertainty of a global LAI modeling for a global carbon cycle model (i.e., the Global Terrestrial Ecosystem Carbon (GTEC) model). Data collected from remote sensing satellites have been used extensively to explore the important components of the terrestrial carbon cycle at regional and continental scales. Recent research efforts have successfully used satellite data to estimate forest LAI across a wide range of biomes (Veroustraete et al., 1996; Goetz and Prince, 1996; Law and Waring, 1994; Ruimy and Saugier, 1994; Gaston et al., 1994; Hunt, 1994; Franklin and Hiernaux, 1991; Nemani et al., 1993; Myneni and Williams, 1994; and Peterson et al., 1987). These efforts have focused on continental and global scale analysis and have used relatively coarse satellite data which is limited in the extent to which it can provide information regarding the variability in carbon cycle dynamics over smaller spatial extents.

The impact of land-use change on the carbon dynamics of vegetation and soil requires not only the information about the present state of the carbon
reservoirs and environmental conditions but also the information about the past land-use. This is due to the fact that the terrestrial ecosystem carbon cycle is a dynamic system that contains pools or reservoirs with several widely different turnover times. It results in the carbon cycle for each field, woodlot or forest, when management conditions are changed, to have transient dynamics that may take several decades to produce new equilibrium conditions. As a result, it is useful to employ a dynamic model to quantify the changes in the various carbon reservoirs through time, especially for the difficulty to measure and observe soil carbon reservoirs. Among many global carbon cycle models, the Global Terrestrial Ecosystem Carbon (GTEC) model (Post et al., 1997) is a powerful tool to calculate the impact of land-use change and changing atmospheric CO2 concentrations and climate variations on the net exchange of carbon between the atmosphere and North Korea forest. GTEC has been used to evaluate the historical exchange of carbon between global terrestrial ecosystems and the atmosphere at a 1 degree latitude and longitude spatial resolution. It combines a production model (Esser, 1984) modified with a process based CO2 fertilization response, an allocation model (Goudriaan and Ketner, 1984), and a decomposition model (Jenkinson, 1990). GTEC’s computational efficiency will work well when applied at the very fine spatial resolution of the remotely sensed data utilized in this proposal. The GTEC model will be employed and modified for each of the major land-cover types for which production and biomass measurements are made. Changes from two time intervals will be used to modify model parameters to more adequately represent conditions of North Korea.

As a conclusion, this study suggests the possibility of LAI modeling of the historical Landsat image based on current reference data set (MODIS LAI/fPAR image and in situ LAI) and geocomputational methodology (SOM-LVQ NN). As this study is carried on with currently available data set, the accuracy of the LAI modeling can be improved significantly with more intensively collected ground-measured reference data and more timely-matched Landsat image. Although this study didn’t try to select the sites and estimate the expected carbon sink of the CDM A/R project of North Korea, the findings of this study show the applicability of remote sensing technology in estimating the expected carbon storage of CDM A/R project by modeling LAI of satellite imagery. As it is extremely difficult to estimate the total carbon
storage of CDM A/R project, many biogeochemical models (i.e., BIOME-BGC) are used to model the expected carbon storage of CDM A/R project and usually require many input data on climate, vegetation, soil, etc. In biogeochemical model, LAI is one of the core data of vegetation. To model the expected carbon storage of CDM A/R project of North Korea, we need not only accurate climate data, but also accurate LAI data of the forest. This study provides general information on the importance of LAI for the monitoring of CDM A/R project and the practical applicability of the historical LAI modeling based on the archived satellite imagery. Future study should focus on the status of North Korea forest in the early 1970's and estimate the change of the cover extend and photosynthetic activity of North Korea forest during the last four decades. The importance of this study is providing empirically-proved theoretical ground for a further refined and elaborated research of the historical LAI change and the carbon sink modeling of the future CDM Afforestation/Reforestation Project of North Korea. This study will help the policy-makers and CDM project managers in the preparation of Afforestation/Reforestation project in North Korea by providing the information of the historical carbon cycle of North Korea forest and empirically tested monitoring methodology of the expected carbon sink from the CDM A/R project of North Korea.
References


Hall, F., Botkin, D., Strebel, D., Woods, K., and Goetz, S., 1991. Large-Scale Patterns of


Appendix

Acronyms
ANN : Artificial Neural Networks
A/R : Afforestation and Reforestation
ASTER : Advanced Spaceborne Thermal Emission and Reflection Radiometer
BIOME-BGC : BioGeochemical Cycles
CDM : Clean Development Mechanism
EVI : Enhanced Vegetation Index
fPAR : fraction of photosynthetically active radiation
GHG : Greenhouse Gas
GTEC : Global Terrestrial Ecosystem Carbon
IET : International Emission Trading
JI : Join Implementation
LAI : Leaf Area Index
Landsat TM : Landsat Thematic Mapper
Landsat ETM : Landsat Enhanced Thematic Mapper
LULUCF : Land-Use, and Land-Use Change and Forestry
LVQ : Learning Vector Quantization
MODIS : Moderate Resolution Imaging Spectroradiometer
MODTRAN : MODerate spectral resolution atmospheric TRANSmittance
NDVI : Normalized Difference Vegetation Index
NN : Neural Networks
NPP : Net Primary Production
SAVI : Soil Adjusted Vegetation Index
SOM : Self-Organizing Map
SRTM : Shuttle Radar Topography Mission
TOA : Top-of-Atmosphere
TSAVI : Transformed Soil Adjusted Vegetation Index
UNFCCC : United Nations Framework Convention on Climate Change
UTM : Universal Transverse Mercator
WDVI : Weighted Difference Vegetation Index
Abstract (in Korean)

The objective of this study is to estimate the area of forest by using Landsat satellite images. The area of forest in the study area was estimated using the Landsat satellite images from 1990 and 2002. The area of forest was calculated using the Landsat satellite images and compared with the results obtained from in situ measurement.

The results showed that the area of forest in the study area increased from 1990 to 2002. The area of forest estimated using the Landsat satellite images was compared with the results obtained from in situ measurement. The area of forest estimated using the Landsat satellite images was found to be higher than the results obtained from in situ measurement.

The accuracy of the estimation was assessed by comparing the results obtained from in situ measurement with the results obtained from the Landsat satellite images. The accuracy of the estimation was found to be satisfactory, and the results obtained from the Landsat satellite images were found to be useful for monitoring the area of forest in the study area.