Assessment of Agricultural Environment Using Remote Sensing and GIS

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ABSTRACT

Remote sensing(RS)- and geographic information system(GIS)-based information management to measure and assess agri-environment schemes, and to quantify and map environment indicators for nature and land use, climate change, air, water and energy balance, waste and material flow is in high demand because it is very helpful in assisting decision making activities of farmers, government, researchers, and consumers. The versatility and ability of RS and GIS containing huge soil database to assess agricultural environment spatially and temporally at various spatial scales were investigated. Spectral and microwave observations were carried out to characterize crop variables and soil properties. Multiple sources RS data from ground sensors, airborne sensors, and also satellite sensors were collected and analyzed to extract features and land cover/use for soils, crops, and vegetation for support precision agriculture, soil/land suitability, soil property estimation, crop growth estimation, runoff potential estimation, irrigated and the estimation of flooded areas in paddy rice fields. RS and GIS play essential roles in a management and monitoring information system. Biosphere-atmosphere interection should also be further studied to improve synergistic modeling for environment and sustainability in agri-environment schemes.

Keywords: mapping, agri-environment, remote sensing, GIS, soil & land, water resources, crop & vegetation, environmental sustainability

INTRODUCTION

Agri-environmental indicator(AEI) is defined as measure of a key environmental condition, risk, or change resulting from agriculture, or of management practices used by producers (McRae et al., 2000). AEIs are becoming more important since environmental sustainability is one of the hottest issues for human quality of life and human economic activity in terms of international interest. Farmers, governments, researchers, environmentalists, and consumers as decision makers are linked with each other and influencing each other in ensuring a sustainable agriculture industry. For instance, management practices of farmers have a direct influence on environmental sustainability, but those decision making activities are influenced by agriculture policy. Information is one of the common needs of all decision makers concerned with agricultural sustainability. Using maps should be a very effective way to provide spatial information to make a decision.

To provide AEIs as a form of map for different users, RS and GIS play essential roles in spatial and temporal assessment of agricultural environment with various spatial scales. RS technologies are used to detect and quantify various field conditions including crops, soils, water, and climate for immediate and future management decisions(Hong et al, 2004). Functional relations have been developed between remote spectral and microwave observations, and crop characteristics and soil properties in various spatial scales(Inoue et al., 2002; Hong et al., 1997; Hong et al., 2000; Hong et al., 2001; Thenkabail et al., 2000; Wood et al., 2002). Image-based RS is an efficient way to detect spatial variability of agricultural fields in land surface. The recent convergence of technological advances in GIS, global positioning systems(GPS), and automatic control of farm machinery have provided an ideal framework for utilizing RS for farm management(Moran, 2000).

One of definitions of GIS is "a computer technology that combines geographic data(the locations of man-made and natural features on the earth's surface) and other types of information(names, classifications, addresses, and much more) to generalize visual maps and reports(O'Looney, 2000)" providing information by modeling. Berry et al.(2003) implied that GIS-based modeling showed relationships within and among mapped data in the 1990s and recently provided logical processing of geospatial information to characterize a system or solve a problem. And he also asserted that there are three basic types of GIS models according to the procedures, which are statistical models based on numerical relationships, suitability models based on logically sequenced decision criteria similar to recipe, and spatial process models. The usefulness of an information system will depend on its providing the decision maker with the right data at the right time in the proper manner.

In this paper, remote sensing and GIS applications for assessing agricultural environment – soil & land, crop & vegetation, water resources – were reviewed, and some opportunities of further studies were discussed.

SOIL & LAND

<Remote sensing principle in soils>

The spectral reflectance of soils has been studied extensively, both empirically with laboratory and field data collection, and theoretically (Baumgardner et al., 1985; Curran et al., 1990; Montgomery & Baumgardner, 1974; Stoner & Baumgardner, 1980). Soil reflectance is a function of the soil's chemical and physical composition (Bowers & Hanks, 1965). Optical properties of soils are related primarily to their mineral composition, since soils result from the physical and chemical weathering of rocks. Soil reflectance is generally low, but increases monotonically with wavelength through the visible and near-infrared regions of the electromagnetic spectrum (Obukhov & Orlov, 1964; Orlov, 1966). Soil color is a useful indicator of soil type and soil properties (Karmanov & Rozhkov, 1972). The spectral reflectance of soils is influenced not only by mineral composition of the parent material and organic matter but also by physical surface conditions (e.g., surface roughness, aggregation), soil constituents (e.g., particle size, iron oxide, soluble salts), observation conditions (e.g., illumination, view direction), and moisture content (Baumgardner et al., 1985; Curran et al., 1990; Hong et al., 1999, Montgomery & Baumgardner, 1974; Stoner & Baumgardner, 1980). Weidong et al. (2002) reported that, at low soil moisture levels, reflectance decreased when moisture increased. However, after a critical point, soil reflectance increased with soil moisture increasing.

<Korean soil information system>

Soil database(DB) based on soil maps surveyed for more than 30 years in Korea with different scales – 1:250,000, 1:25,000, 1:5,000 – was established to provide valuable soil information of the whole country for feature extraction and for various land surface models(asis.rda.go.kr). Soil attributes with the graphics of soil boundaries provided in the digital soil maps are soil texture, gravel content, drainage, available soil depth, slope, topography, parent material, land use for the time of soil survey, soil suitability group for paddy, upland, and orchard, soil classification regimes, and the like. Each soil property can be provided as a form of map showing spatial distribution with statistics such as sum and average of the attributes.

<Applications>

■ Widespread implementation of precision agriculture in the countries which have large size farms will require methods for more efficiently and economically characterizing variations in soil properties and other factors that affect crop yields. In operational precision agriculture, soil chemical property variability is usually characterized by soil sampling on a relative coarse grid, laboratory analysis, and statistical interpolation. These procedures are costly, time-consuming, and provide relatively low-resolution data. Methods that could estimate soil chemical properties with more efficiency and higher spatial resolution would appeal to producers short on time and/or funds to use for soil sampling. Soil texture can also vary considerably within fields, leading to differences in productivity due to variability in soil water holding capacity and other parameters important for crop growth. In general, soil chemical properties were negatively correlated with reflectance in the visible and near infrared region(Fig. 1). Blue wavelengths were most strongly related to ground-measured soil properties, including chemical properties (Fig. 1), clay content, and soil EC_a. Principal component(PC) 4 and PC 1 from the 2000 and 2002 bare soil images (dry soils) were highly correlated to soil chemical properties and EC_a, respectively. Bare soil images obtained in dry conditions (2000 and 2002) were useful for estimating soil chemical properties and EC_a whereas the moist soil (2001) image was appropriate for estimating soil texture.

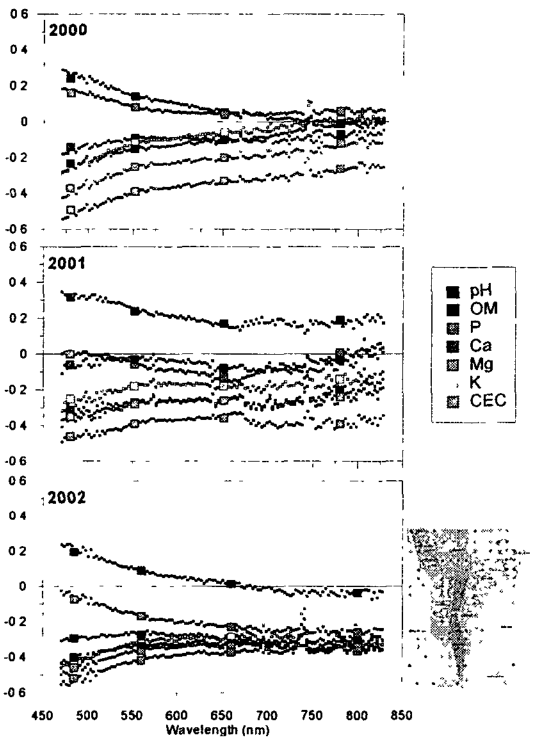

Figure 1. Correlations of 120 hyperspectal wavelengths and four Landsat-like bands (LLBs, larger symbols) to chemical properties(left) and sampling grid(right).


Figure 2. Soil sampling to estimate inter-field soil variability (Quickbird, 2004.10.27) (up) and farm land unit map (bottom) in a rice plain in Dangjin, Korea.

■ In Korea, the average size of farm land is about 0.5 ha for paddy rice fields and much lesser for upland dry fields. Inter-field variability is bigger and more acceptable for management practice in Korea than within-field variability to estimate soil properties. Soil samples were taken irregularly at about 3.5 ha interval for the area(500 ha) of a rice plain to compare soil chemical properties such as organic matters with digital numbers of remotely sensed imagery as shown in Fig. 2. Field management such as tillage and rice straw management after harvest influenced the land surface signatures of remotely sensed data. Tilled fields looked darker than the other fields since moist soil turned over was exposed. The color of soil looks darker as the soil becomes wetter, in general. Field signature data from the imagery based on farmland polygons as shown at the bottom of Fig. 2 need to be compared with remote sensing data as well as point data extracted from the imagery.

■ The landcover map of Korean peninsular with temporal Lansat-5 and Lansat-7 images taken in spring and fall was made using supervised classification, unsupervised classfication, and the level slicing technique for water body detection. North Korea is inaccessible for ground truth and little information on its land surface cover is available so considering the surface condition of South Korea, hybrid classification was applied because it provided a relatively high classfication accuracy and smooth error adjustment. Land cover of the Korean peninsular was divided into paddy field, upland field, forestry, grassland, barren·desolation land, water, and man-made structure (Fig. 3). Geographically explicit land use data based on RS images with high spatial resolution of a country will be in high demand to produce appropriate data supporting international agreements such as land use, land-use change and forestry(LULUCF) for intergovernmental panel on climate change(IPCC). IPCC defines cropland as the category that includes arable and tillage land, and agro-forestry systems in which vegetation falls below the thresholds used for the forest land category, consistent with the selection of national definitions. Cropland inventory based on RS images and GIS needs to be established to support not only government but also farmers for the framework of environmental sustainability in agriculture.

Figure 3 Land cover classification map of Korean peninsular using Landat (+E)TM data.

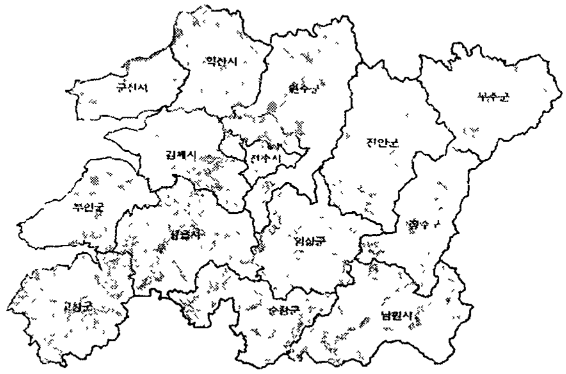

Figure 4. Soil suitability maps proposed for all cropland types (paddy rice, upland, and orchard) in Jeonbuk province.

■ Soil suitability for all cropland types (paddy rice, upland, and orchard) as a food production basis in Jeonbuk province was assessed using soil information database(1:5,000) of Korea provided by National Institute of Agricultural Science and Technology(NIAST), RDA. A simple criterion was adopted to extract the areas that showed less than grade 4 for all cropland types as shown in Fig. 4. It was a binary model as to each cropland type, which identifies areas that are acceptable based on combining binary maps (0 and 1). Two more models for the suitability model are a ranking model which develops a ranking of areas based on the number of criteria that are acceptable (e.g. 1 to 3) and a rating model which develops a "goodness" scale (e.g. 0 to 9 best) and calculates the average rating for each grid cell.

CROP & VEGETATION

<Remote sensing principle in vegetation>

Vegetation is one of the most important components of ecosystem. The place of reaction to reflect electromagnetic energy in vegetation is the leaf. The chlorophyll pigments in the palisade parenchyma cells have a significant impact on the absorption and reflectance of visible light (blue, green, and red), while the spongy parenchyma mesophyll cells have a significant impact on the absorption and reflectance of near-infrared incident energy(Jensen, 2000).

Vegetation indices (VI) are dimensionless, radiometric measures that function as indicators of relative abundance and activity of green vegetation. A vegetation index should maximize sensitivity to plant biophysical parameters, normalize or model external effects such as sun angle, viewing angle, and the atmosphere, and normalize internal effects such as canopy background variations. In spectral signature analysis by remote sensing, vegetation indices that combine red and near-infrared bands are widely used for estimating the vitality and the productivity of vegetation. The cellular structure of leaf mesophyll strongly scatters and reflects near-infrared energy. In the visible region, vegetation looks dark on the imagery because of the high absorption of pigments such as chlorophyll, xanthophylls, and the like. Vegetation indices are generally based on empirical evidence, not on basic biology, chemistry or physics.

Leaf area index (LAI) was first introduced by Watson (1947) and defined as the ratio of leaf area to a given unit of land area, a ratio that is functionally linked to spectral reflectance. LAI plays an important role in explaining the ability of the crop to intercept solar energy and in understanding the function of many crop management practices. Many have attempted to develop relationships between vegetation indices and LAI and have discussed their potential and limitations (Baret and Guyot, 1991; Wiegand et al., 1991; Thenkabail et al., 2000).

<Applications>

■ Amount of chlorophyll a and b in the leaf is closely related to leaf nitrogen contents and agronomic parameters including LAI, total dry matter. Both leaf chlorophyll amount and nitrogen content were inversely related to the visible wavelengths and correlated to the ratio of near infrared and green wavelengths (Fig. 5, Hong et al., 1997). Leaf nitrogen content and grain protein content of rice canopy in a region can be estimated to support the decision for appropriate amount of fertilization and the time of harvest Inter-field spatial variability of rice growth and development is more obvious than within-field variability in the rice field condition as shown in Fig. 6. Field data were collected using an active sensor measuring biomass and NDVI during the day of image acquisition for inter-comparison of crop growth, sensor values, and satellite image data.

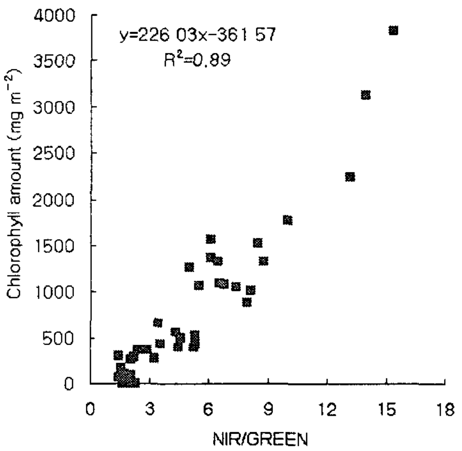

Figure 5.
Relationship between chlorophyll amount of rice canopy and the ratio of NIR and green wavelengths before heading stage in 1997

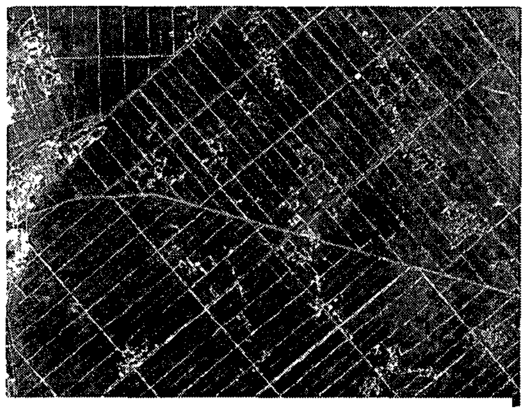

Figure 6.
Spatial variability of rice growth with different varieties or cultivars (Orbview image taken on June 24, 2005)

■ Image-derived vegetation indices and crop models were used to estimate and simulate LAI, and data were compared with measured LAI data for both corn and soybean(Fig. 7). Over the growing season, the general trend in NDVI was similar to that in LAI. Measured LAI could be expressed as a function of image-derived vegetation indices such as NDVI, RVI, and SAVI using LAI and image data(Hong et al., 2004). In general, vegetation indices over-estimated LAI in early growth stages and under-estimated it after the grain or pod filling stage, probably due to saturation of the VI-LAI relationship(Hong et al., 2004). NDVI showed a strong variation over the growing season, as did LAI. Curvilinear relationships between NDVI and leaf area index (Fig. 8) were found with the data obtained throughout the growing season at monitoring sites within a corn field.

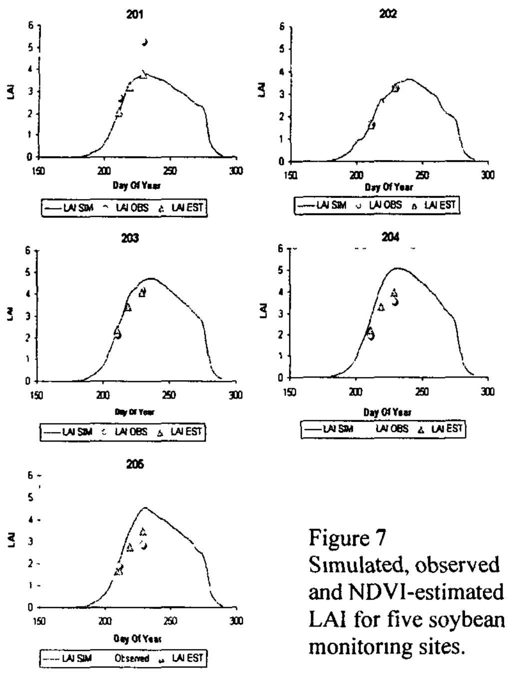

Figure 7
Simulated, observed and NDVI-estimated LAI for five soybean monitoring sites.

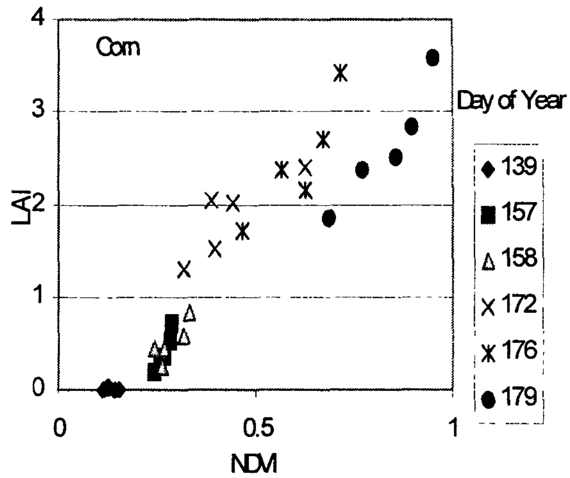

Figure 8.
Relationship between LAI and NDVI for corn over several dates in 2002

■ Radar remote sensing has advantages such as all-weather imaging capability and day/night acquisition. Temporal radar backscatter signatures of rice canopy in the growing season showed an increasing trend as growth advanced until the end of vegetative stage ranged from –16 dB to –3.1 dB(Fig. 9 and 10). Then they stayed on the plateau until the end of ripening stage. Second order polynomial relationship was found between backscattering coefficient and LAI(Fig. 11) and dry biomass(Fig. 12).

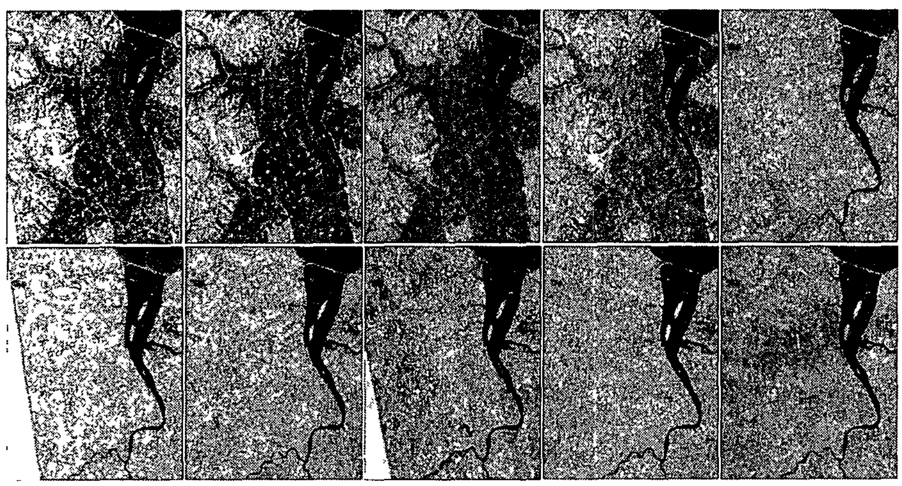

Figure 9
Temporal variation of backscatter signatures of RADARSAT images during the growing season in 1999.

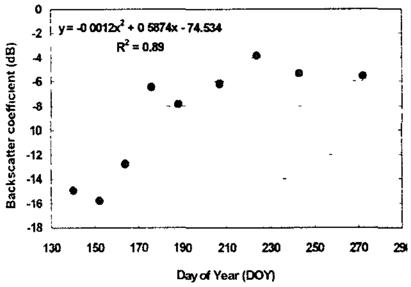

Figure 10
Temporal RADAR backscatter signatures of rice during the growing season as a function of time

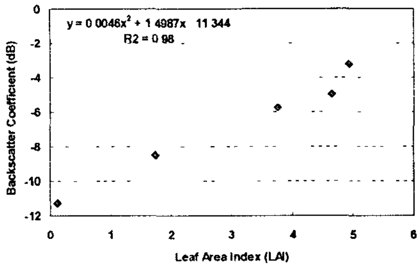

Figure 11.
Temporal RADAR backscatter signatures of rice as a function of LAI before heading stage

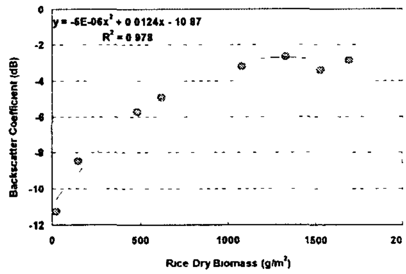

Figure 12.
Temporal RADAR backscatter signatures of rice as a function of dry biomass

WATER RESOURCES

<Remote sensing principle in water>

The best wavelength region for discriminating land from pure water is the near-infrared and middle-infrared regions at wavelengths between 740~2,500 nm. In the near- and middle-infrared regions, water bodies appear very dark, even black, because they absorb almost all of the incident radiant flux, especially when the water is deep and pure with no suspended sediments or organic matters in it. Conversely, land surfaces are typically composed of vegetation and bare soil that reflect a significant amount of near- and middle-infrared energy. This causes the land surfaces to appear relatively bright in near- and middle-infrared bands of imagery(Jensen, 2000).

<Hydrological modeling in GIS>

Elevation, elevation derivatives(slope, aspect, drainage flow direction) and land cover data are required for modeling the physical process of the hydrologic cycle. There are three major types of deterministic models: empirical lumped models, empirical distributed models, and physically-based distributedmodels. Empirical models are based on regression and correlation results from statistical analyses of time series data. Physical models are based on formulas of physical relations. Lumped models are mainly used in rainfall-runoff modeling. Distributed hydrological models are supposed to describe flow process in each and every point inside a catchment(Olsson and Pilesjö, 2002).

<Applications>

■ Curve number indicates the runoff potential of the area. The SCS curve number method is a simple, widely used and efficient method for determining the approxient amount of runoff from a rainfall event in a particular area(Mishra and Singh, 1993). The curve number is based on the area's hydrologic soil group, land use, treatment, and hydrologic condition. The two former characters are of greatest importance. Spatial variability from land use/cover and soil hydrological properties including infiltration rate during the crop growing season at a field level in agricultural land should be taken into account to estimate runoff. The watershed of the study is located in Goesan-gun including Sosu-myeon (approx. 7,630 ha), Chungchungbuk-do. Using a digital elevation model(DEM), the watershed and the catchments were delineated. The research classified Korean soils into 4-5 hydrologic soil groups based on infiltration rate measured and an estimation model for the representative soils of the restudy area. Digital soil maps(1:5,000 scale) were used for classifying hydrologic soil groups based on soil series unit. On-screen digitization using high resolution aerial images, each field boundary was delineated as farm land unit. After land use and cover survey was carried out for every field, farm land unit data were used for curve number calculation in the watershed. Curve number (CN) was calculated for estimating runoff in the watershed using the land use/cover map and the hydrologic soil map. CN values of the catchments in the watershed ranged from 35 to 57(Fig. 13). CN values of each farm land cells ranged from 20 to 98, in the order of forest, paddy fields, upland, and village or man-built area which showed the highest imperviousness. Fig. 14 showed CN values of each farm land cell in different cropland types on the topographic representation of the Quickbird image taken on Oct. 16, 2004.

Figure 13.
CN values of catchments in the watershed.

■ To classify irrigated rice paddy field, sequential RADARSAT images (5.3 GHz/C-band 5.6 cm, HH polarization) were obtained by shallow incidence angle(standard beam mode 5 or 6) during the growing season. Radar backscatter coefficients (σ^{o}) were extracted by calibration process and then the imagery were registered and resampled. For paddy field mapping, Lee filter, 5x5 window size, and 2 iterations were chosen for speckle noise reduction. Informative layers - May 20, June 13, and July 25 - for rice field mapping were selected by optimum index factor(OIF) calculation. Rice-planted area was classified by ISODATA(Iteratice Semf-Organizing Data Analysis Technique) with selected three-dates data and compared with the rice field map using Landsat TM images(Fig. 15).

	평탄지 논 (경지정리)	곡간지 논 (경지정리 안됨)	곡간지 밭	평탄지 밭	휴경지
면적(km²)	603.39	398 43	394 67	228 50	39 32
필지수	818	1 072	1 828	280	180
수문유형별 CN값 (A/B/C/D)	59/70/78/81	58/69/78/80	62/71/78/81	64/74/81/85	76/65/90/93 74/83/88/90
평균 CN	60	58	61	64	72
Quantile별 CN값	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 14.
CN values of each farm land cell in different crop types.

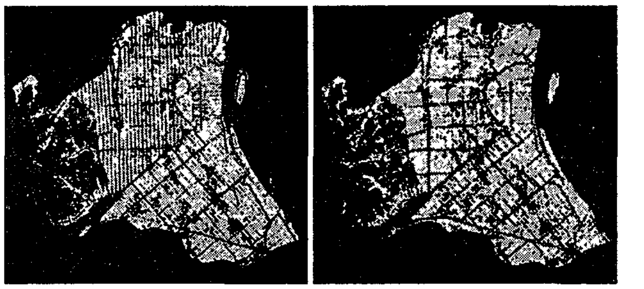

Figure 15.
Rice-planted area discriminated a) from three-dates RADARSAT data by unsupervised classification and b) from two-dates Landsat TM imagery by rule-based classification (Hong *et al.*, 1999) (Woogang-myeon, Dangjin-gun, Chungnam province, Korea).

CONCLUSIONS

An overview of remote sensing and GIS applications has been given in the fields of soil & land, crop & vegetation, and water resources for assessing agricultural environment. Soil and land management information can be obtained using remotely sensed data by ground and remote sensors in the sky from sub-field to regional scale. Land use/cover inventory mainly focusing on the classification of cropland types should be established and updated on a regular basis to provide base maps for quantifying agri-ecosystem phenomena such as carbon estimation and statistical data of food production and productivity of the country in agriculture. As monitoring tools of natural disasters, remote sensing and GIS provide historical database on a map basis and help to predict possible vulnerable areas at national, regional, local, and field levels. Soil-vegetation-atmosphere interaction also must be studied to understand the dynamics and the balance of energy and water in the agro-ecosystem. Temporally and spatially assessed agri-environment information as a form of map using RS and GIS will greatly assist decision makers in establishing policy, crop management practices, and integrating all the information effectively and efficiently. Observing and understanding the agri-environmental systems provides a fundamental basis essential for enhancing human health, safety, and welfare, and bringing harmony between man and nature.

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