INTEGRATING REMOTELY SENSED DATA WITH AN ECOSYSTEM MODEL TO ESTIMATE CROP YIELD IN NORTH CHINA

P. Yang [a, b, *], G.X. Tan [a], Y. Zha [b], R. Shibasaki [a]

[a] Institute of Industrial Science, Tokyo University, Tokyo 153-8505, Japan
yangpeng@iis.u-tokyo.ac.jp, (gxtan, shiba)@skl.iis.u-tokyo.ac.jp
[b] Institute of Natural Resources & Regional Planning, Chinese Academy of Agricultural Sciences
Beijing 100081, China - yzha@caas.ac.cn

Commission VII, WG VII/2

KEY WORDS: Remote Sensing, Agriculture, Crop, Estimation, Integration, Model, Accuracy, GIS

ABSTRACT:

This paper describes a method of integrating remotely sensed data (the MODIS LAI product) with an ecosystem model (the spatial EPIC model) to estimate crop yield in North China. The traditional productivity simulations based on crop models are normally site-specific. To simulate regional crop productivity, the spatial crop model is developed firstly in this study by integrating Geographical Information System (GIS) with Environmental Policy Integrated Climate (EPIC) model. The integration applies a loose coupling approach. Data are exchanged using the ASCII or binary data format between GIS and EPIC model without a common user interface. It is crucial for the simulation accuracy of the spatial EPIC model to get the detailed initial conditions (sowing date, initial soil water content, etc) and management information (irrigation schedule, fertilizer schedule, tillage schedule, etc). But when applied at a large scale, the initial conditions and management information are most unlikely obtained through direct measurement. Therefore, the spatial EPIC model is integrated secondly with the MODIS LAI product from the Earth Resources Observation System (EROS) Data Center Distributed Active Archive Center. The integration of the MODIS LAI product makes the real time information taken into account in the simulation of spatial EPIC model, such as the amount of solar radiation captured by plant canopies, soil-water or nutrient effects on crop growth, and the effects of natural or man-made disturbances caused to crop yield. Finally, the method is conducted to estimate the Winter Wheat yield in North China in the year of 2003.

1. INTRODUCTION

Monitoring agricultural crop conditions during the growing season and estimating the potential crop yields are both important for the assessment of seasonal production (Paul et al. 2003). The accurate and real-time estimation of crop yield in provincial and national level are of great interest to the Department of Agriculture in many countries. Integrating of satellite data and crop productivity models is one of the most important quantitative analysis methodologies for yields estimation in regional level.

The traditional crop yield estimation based on satellite data is using the empirical relationships between dry biomass of various crops and Vegetation Indices, which are combinations of visible and near infrared bands. Hamar et al. (1996) established a linear regression model to estimate corn and wheat yield at a regional scale based on vegetation spectral indices computed with Landsat MSS data. Similar relationships are obtained on various crops (for example: Rasmussen [1992] for millet yield, Manjunath et al. [2002] for wheat yield). Although the VI approach is simple, the relationships only have a local value and are sensitive to soil and atmospheric conditions as well as measurement geometries. To estimate crop yield in any conditions, it is necessary to describe the physiological and biological mechanisms, which control crop growth and development (Moulin et al. 1998). Therefore various mechanistic models are inevitable to be integrated with remote sensing data for yield assessment of major crops in regional scale.

Mechanistic models can simulate the time profiles of the crop state variables (leaf area index, crop stress factor, potential biomass increase etc.) and of energy, carbon, water and nutrient fluxes at the crop-soil-atmosphere interfaces. For more than three decade, mechanistic models have been developed for the major crops in the world. Compared with many other crop models around agro-ecosystems, the EPIC Model seems to be more suitable to simulate crop yields for relative comparisons of soils, crops, and management scenarios and has a good accuracy to estimate field yields (Tan et al. 2003). It was originally developed by United States Department of Agriculture to examine the relationship between soil erosion and agricultural productivity. The model integrates the major processes that occur in the soil–crop–atmosphere–management system, including: hydrology, weather, erosion, nutrients, plant growth, soil temperature, tillage, plant environmental control, and economics (Sharpley et al. 1995). Extensive tests of EPIC simulations were conducted at over 150 sites and on more than 10 crop species and generally those tests concluded that EPIC adequately simulated crop yields (Easterling et al. [1998], Izaurralde et al. [2003]).

The different ways to integrate a crop model with the radiometric observations were described initially by Maas (1988). Delecolle et al. (1992) and Moulin et al. (1998)

* Corresponding author. Tel.: +81-3-5452-6417; Fax: +81-3-5452-6414; E-mail address: yangpeng@iis.u-tokyo.ac.jp

identified them into four integration methods: the direct use of a driving variable estimated from remote sensing information; the updating of a state variable of the model; the re-initialization of the model; and the re-calibration of the model. The temporal resolution of remote sensing data is so difficult to reach the time step requirement of crop models (from daily to weekly) that the direct use of a driving variable method is rarely the case. But the other three methods have been tested. Reynolds et al. (2000) developed an operational crop yield model in Kenya by introducing real-time satellite imagery into a GIS and the Crop Specific Water Balance (CSWB) model of FAO. Clevers et al. (1996) used ground and airborne radiometric measurements over sugar beet fields to calibrate the SUCROS model. The adjusted parameters and initial conditions were sowing date, a growth rate, light use efficiency and maximum leaf area. More current researches were focused on estimating LAI from optical remote sensing data, because LAI is the key variable during the whole yield simulation in most of the mechanistic models. Guerif et al. (2000) coupled the radiative transfer model SAIL with the crop model SUCROS to re-estimate crop stand establishment parameters and initial conditions for sugar beet crops. Paul et al. (2003) used the SAIL model to link the EPIC model with satellite data in the spring wheat yield estimation of North Dakota. It was evident that how to measure or estimate the input parameters describing crop canopy characteristics in regional level for radiative transfer model is the key factor for coupling radiative transfer model to crop models. If the standard LAI product acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) can be validated and be proved to be suit for integration of crop productivity models, the operational yield assessment in regional level will be available.

The objective of this study is to develop one operational crop yield model in regional level (North China) that integrates the USDA (United States Department of Agriculture) EPIC (Erosion Productivity Impact Calculator) model with NASA MODIS LAI product, ground-based ancillary data, and a Geographical Information System (GIS).

2. STUDY AREA

The study area is North China, which includes Beijing and Tianjin, the two municipalities, Hebei, Shanxi, Shandong and Henan Provinces (Figure 1). The area studied is 110°E-123°E longitude by 30°N- 43°N latitude and about 0.69 Million km^2.

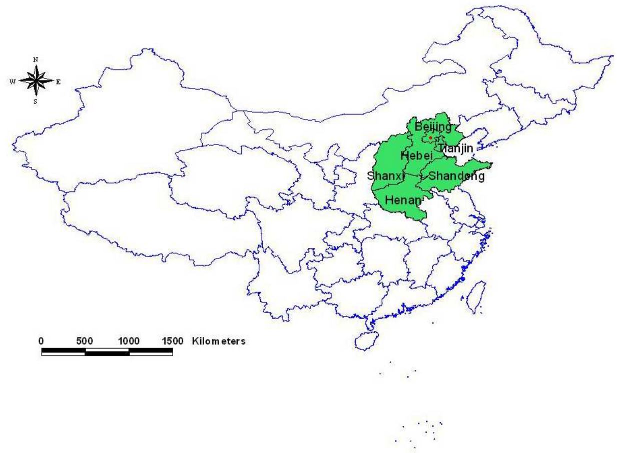

Figure 1. The study region of North China covers a 6.9×10^5 km^2 area (110°E-123°E longitude and 30°N-43°N latitude)

The North China lies in semi-arid and semi-humid zone with an annual temperature sum of some 4800°C (>0°C), a spatially and temporally strongly variable annual precipitation sum of some 600 mm and cumulative annual radiation around 5200MJ/m^2. The area is one of the most important grain production bases of China and plays an important role in the national food security. The population, cultivated land and crop production in 2000 have been reached to 24%, 22% and 25% of the national total respectively. The most widely distributed crops in North China are wheat in winter and corn in summer.

3. METHODOLOGY

In this section, the crop productivity model (EPIC model) used in the analysis, the method for integrating GIS with EPIC model, and the processing method of combining MODIS LAI product to spatial EPIC model are described.

3.1 EPIC Model

EPIC operates on a daily time step to simulate evapotranspiration, soil temperature, crop potential growth, growth constraints (water stress, stress due to high or low temperature, nitrogen and phosphorus stress) and yield. EPIC uses a single model for simulating all crops, each crop has unique values for model parameters, which can be adjusted or created by the user as needed. The crop growth model uses radiation-use efficiency in calculating photosynthetic production of biomass. The potential biomass is adjusted daily for stress from the following factors: water, temperature, nutrients (nitrogen and phosphorus), aeration and radiation. Crop yields are estimated using the harvest index concept. Harvest index are calculated from accumulated Leaf Area Index (LAI), which increases as a non-linear function of heat units from zero at the planting stage to the maximum value and then declines from the maximum value to the low value or zero at maturity. The harvest index may be reduced by high temperature, low solar radiation, or water stress during critical crop stages. Therefore, LAI is one of the most important variables in EPIC model, which influences the simulation for Photosynthetic Active Radiation (PAR); Potential Biomass Increase; Harvest Index and Crop Yield.

3.2 Integrating GIS with EPIC Model

In order to facilitate the storage, manipulation, and handling of complex EPIC spatial information, it is necessary to input all raw spatial data into a geographical information system. The data handling and analysis, which involves data editing, conversion, interpolation, and overlay, can lead to the application of GIS. With the aid of GIS, it is possible for the EPIC to simulate crop yields efficiently at regional scale, and to allow a flexible presentation of results according to the user's needs.

There are several different approaches to integrate GIS with simulation models, such as the embedding method, loose coupling, and the tight coupling method. In this study, the loose coupling approach was used to integrate GIS with the EPIC. This approach uses two different packages directly. One is a standard GIS package (Arcview GIS3.2) and another is EPIC program (EPIC version 8120). They are integrated by combining various data layers on the physical aspects of agricultural environments such as soil, landform, and climate, via data exchange using either ASCII or binary data format between these two packages, which do not have a common user interface. The advantage of this approach is that redundant programming can be avoided. Map input, data handling, spatial analysis, and map output capabilities of GIS are used for the preparation of the land resource database required by the EPIC. The EPIC processing is outside of the GIS.

3.3 Combining Spatial EPIC Model and MODIS LAI Product

The integration of MODIS LAI product with the spatial EPIC model is achieved by using two distinct methods. The first method is the updating of LAI value in EPIC model. The LAI value simulated by EPIC model in some key stage of crop growth is updated by using the MODIS LAI product directly. In the second method, the time series of MODIS LAI product is used to calibrate the spatial EPIC model. Calibration was performed to adjust some model parameters: the maximum potential LAI of the crop; the leaf area decline rate (RLAD); and the time when green LAI begins to decline (DLAI).

4. MATERIALS AND DATA REQUIREMENTS

The MODIS LAI product and some important input data for EPIC model, such as weather, soil, and management data, are introduced here.

4.1 Weather Data

EPIC uses a stochastic weather generator to generate daily weather from monthly climatic parameters. The basic data set needed for each site is a record of monthly maximum and minimum temperatures, precipitation, Standard Deviation (S.D.) of maximum daily air temperature, S.D. of minimum daily air temperature, S.D. of daily precipitation, skew coefficient for daily precipitation, probability of wet day after dry day, and probability of wet day after wet day. The weather data from year 1981 to 1990 in this study is from Global Daily Summary produced by National Climatic Data Center from 256 available terrestrial stations in China. This history weather data were used to validate the spatial EPIC model. When the MODIS LAI product is integrated with the spatial EPIC model in order to estimate winter wheat yield of North China in 2003, data from more than 200 weather stations of North China will be applied. Kriging method aided by climatologically and topographically interpolation with quality control model is applied (Tan et al. 2002).

4.2 Soil Data

EPIC can accept up to 20 parameters for 10 soil layers. However, only a minimum of seven parameters is required: depth, percent sand, percent silt, bulk density, PH, percent organic carbon, and percent calcium carbonate. Other soil parameters can be estimated by EPIC itself. Therefore only these seven parameters in four layers are applied in this study. The soil-depth intervals are 0–0.1, 0.1–10, 10–30, 30–50, and 50–80 cm. All soil databases are provided by the Global Soil Task cooperated by the Data and Information System (DIS) framework activity of the International Geosphere–Biosphere Programme (IGBP) (Scholes et al. 1995). The highest spatial resolution of this database is 5 min × 5 min (about 6km × 6km).

4.3 Management Data

EPIC requires detailed descriptions of management practices. These descriptions must specify the timing of individual operations either by date or by fraction of the growth period (i.e. by heat units). EPIC allows the user to simulate complex crop rotations with a variety of irrigation, fertilizer, pesticide, and tillage control options. There are two options for irrigation and fertilizer scheduled application in the EPIC program: manually and automatically. Only the manual option is applied in the spatial EPIC model. Some parameters of manual mode are described in details in Table 1 (Huang et al. 2001). The land use map at the scale of 1:1,000,000 is made by the Australian Center of the Asian Spatial Information and Analysis Network, Griffith University.

Table 1. The Operation Parameters of Winter Wheat – Summer Corn Rotation for EPIC Model in North China

SUMMER CORN			WINTER WHEAT		
Date	Operation	Volume	Date	Operation	Volume
Jun. 20	Irrigation	40mm	Oct. 8	Irrigation	40mm
Jun. 20	Fertilizer	72kg/ha*	Oct. 8	Fertilizer	72kg/ha*
Jun. 23	Planting		Oct. 8	Fertilizer	55kg/ha**
Aug.10	Fertilizer	48kg/ha*	Oct.10	Planting	
Sep.28	Harvest		Apr.10	Irrigation	100mm
			Apr.20	Fertilizer	48kg/ha*
			May10	Irrigation	100mm
			Jun.18	Harvest	

Note: "*" means the application amount of 100% nitrogen in chemical fertilizer.
"**" means the application amount of 100% phosphorus in chemical fertilizer.

4.4 MODIS LAI Product

The MODIS LAI-FPAR algorithm is based on three-dimensional radiative transfer theory and developed for inversion using a look-up table (LUT) approach (Myneni et al. 2002). According to the algorithm, global vegetation is classified into six canopy architectural types: grasses and cereal crops, shrubs, broadleaf crops, savannas, broadleaf forests and needle leaf forests. The structural characters among these biomes, such as the horizontal (homogeneous vs. heterogeneous) and vertical (single- vs. multi- story) dimensions, canopy height, leaf type, soil brightness and climate (precipitation and temperature), are used to define unique model configurations, including some fixed parameter values appropriate for the biome characteristics. LUTs are then generated for each biome by running the model for various combinations of LAI and soil type. The algorithm ingests atmospherically corrected bi-directional reflectance factors, their uncertainties and corresponding sun-view geometries. It compares the observed reflectances to comparable values evaluated from model-based entries stored in LUTs and derives the distribution of all possible solutions. When this method fails to identify a solution, a back-up method based on relations between the normalized difference vegetation index (NDVI) and LAI and FPAR is used.

The current MODIS 1-km LAI-FPAR product is retrieved from the reflectances of two bands (648 and 858 nm) and on an 8-day compositing period. The product also includes extensive quality control (QC) information regarding cloud and data processing conditions. During each 8-day period, the highest-quality LAI and FPAR are selected. These data are further composited over 4 (or 3) consecutive 8-day periods to produce monthly data (Tian et al. 2004). This study uses the MODIS LAI product from Sep. 2002 to Jul. 2003, which was downloaded from the home page of Myneni`s Climate and Vegetation research group in the Department of Geography at Boston University (available ftp://crsa.bu.edu/pub/rmyneni/myneniproducts/datasets/MODIS/MOD15_BU/C4/).

5. RESULTS AND DISCUSSION

5.1 Validation of the Spatial EPIC Model

The average yield of winter wheat and summer corn in North China for 1980s, simulated by the spatial EPIC model, can be seen from the Figure 2 and 3. The simulated yields are just compared with the statistical yields from the China Statistical Yearbook from 1982-1991, due to the lack of the actual yield data. The Table 2 shows the comparison results. The differences in percentage between simulated and statistical yield are mostly under 10%, except the situation in Beijing and Shandong. It is evident that crop yield of the area is underestimated by the spatial EPIC model, especially for Beijing. The reason is that Beijing and Shandong is the developed region in North China. The cropland in these regions are applied a very good field management with a better irrigation condition, fertilizer condition and so on. But only the simple and ordinary field operation parameters are inputted into the spatial EPIC model, which result in the underestimating situation. If the EPIC crop parameters established by USDA can be adjusted to be suitable for the application in North China, and the detailed field management information, such as the cropping system, irrigation schedule, fertilizer schedule and tillage schedule, can be obtained and be inputted into the spatial EPIC model. It should be possible to improve the simulation accuracy.

Table 2. Comparison between the simulation yield from spatial EPIC model and the statistical yield (Ton/hectare)

Region	SUMMER CORN			WINTER WHEAT		
	Simulated	Statistical	Error	Simulated	Statistical	Error
BeiJing	2.979	4.820	38.2%	2.598	3.959	34.4%
TianJin	3.686	3.864	4.6%	2.812	2.829	0.6%
HeBei	3.647	3.623	0.7%	2.654	2.965	10.5%
ShanDong	3.639	4.356	16.5%	2.669	3.388	21.2%
HeNan	3.706	3.323	11.5%	3.002	3.322	9.6%
ShanXi	3.796	3.993	4.9%	2.528	2.576	1.9%

Note: "Simulated" means yield simulated by model; "Statistical" means the average statistical yield from the China Statistical Yearbook from 1982-1991.

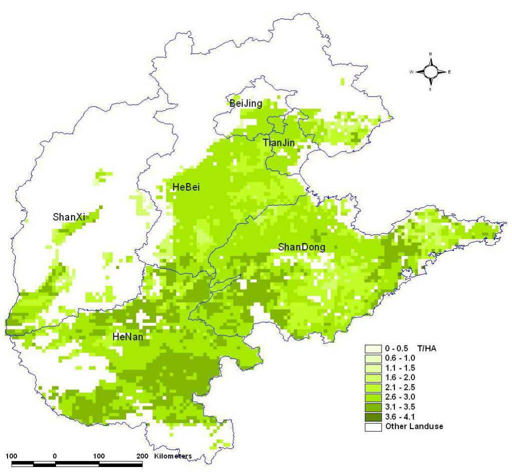

Figure 2. The simulated yield per hectare of winter wheat by spatial EPIC model in North China

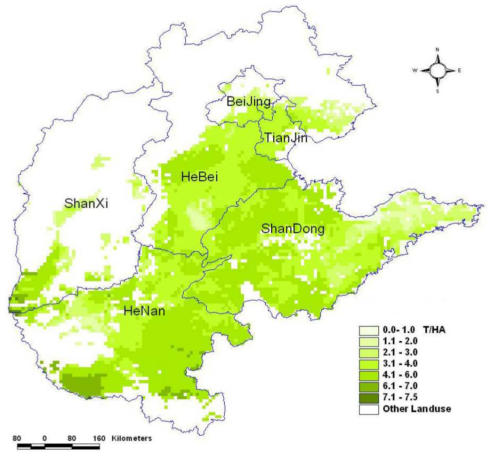

Figure 3. The simulated yield per hectare of summer corn by spatial EPIC model in North China

5.2 Validation of Combining the Spatial EPIC Model and MODIS LAI Product

Winter wheat – summer corn rotation is the dominant cropping system in North China. According to ground observation data, the key crop phenological stages are emergence (October), recovering (February), heading (May), maturity (June) of winter wheat and emergence (June or July), tasseling (August), maturity (October) of summer maize. The maturity of winter wheat and the sowing of summer maize usually occur within 20 days. The leaf area index should reach maximum values during the heading (winter wheat) and tasseling (maize) stages. The colour-coded images of monthly MODIS LAI product for East Asia from year 2002 (September) to year 2003 (August) are shown in figure 4. From the consecutive images of monthly LAI in one year, it is evident to see the change profile of LAI value. But temporal resolution seems to be impossible to retire the model parameters to calibrate the spatial EPIC model. The higher resolution MODIS LAI product in 8-days or daily in some key stage should be obtained for the integration. Therefore, the validation of combining the spatial EPIC model and MODIS LAI product is not conducted yet.

6. CONCLUSIONS

The operational methodology of crop yield assessment in regional level was introduced in this study by integrating EPIC model with NASA MODIS LAI product, ground-based ancillary data, and GIS. The spatial EPIC model was developed and validated in North China firstly. The result indicated that the spatial EPIC model could simulate crop yield efficiently at regional level. But crop management information required by model, such as planting time, irrigation schedule and fertilizer schedule et al., is crucial for simulation accuracy and is not available by field measurement. Satellite remotely sensed data cans provide a real-time assessment of the magnitude and variation of crop condition parameters. Therefore the methodology of combining MODIS LAI product with Spatial EPIC model to improve yield simulation accuracy was built secondly, but it was not conducted and validated due to be lack of the necessary input data set yet.

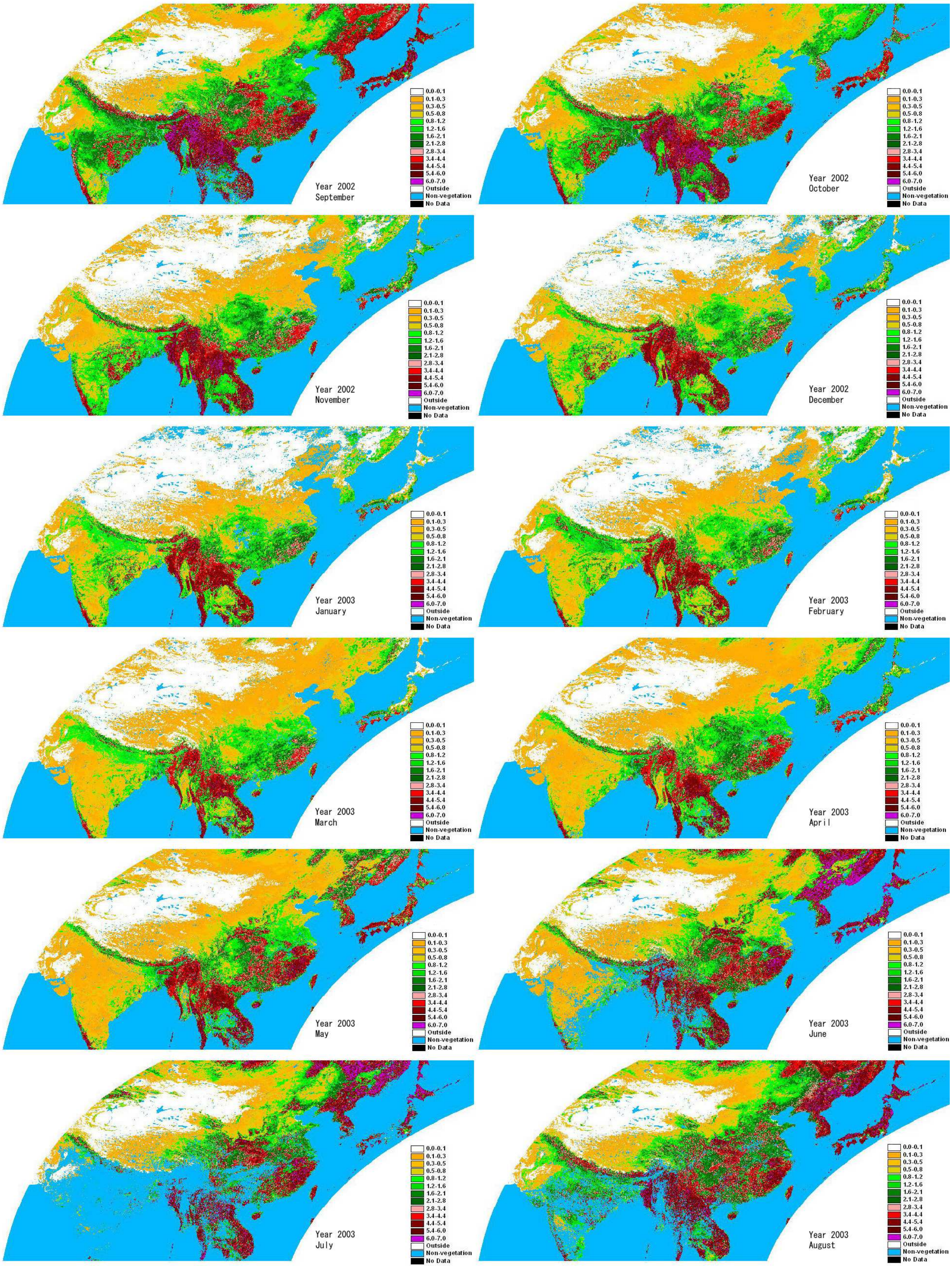

Figure 4. Colour-coded images of monthly MODIS LAI product for East Asia from year 2002 (September) to year 2003 (August)

ACKNOWLEDGEMENTS

This study was funded partly by the National High Technology Research and Development Program of China (2003AA131020). The authors gratefully acknowledge the technical support and expert advice from Dr. Tang Huajun, Dr. Zhou Qingbo, Dr. Chen Youqi and Dr. Chen Zhongxin in Key Laboratory of Resources Remote Sensing & Digital Agriculture, Ministry of Agriculture, China.

REFERENCES

Clevers, J.G.P.W., and van Leeuwen, H.J.C., 1996. Combined use of optical and microwave remote sensing data for crop growth monitoring. *Remote Sensing of Environment*, 56, pp. 42-51.

Delecolle, R., Maas, S. J., Guerif, M., and Baret, F., 1992. Remote sensing and crop production models: present trends. *ISPRS Journal of Photogrammetry and Remote Sensing*, 47, pp. 145-161.

Easterling, W.E., Weiss, A., Hays, C.J., Mearns L.O., 1998. Spatial scales of climate information for simulating wheat and maize productivity: the case of US Great Plains. *Agric. For. Meteor*., 90, pp. 51-63.

Guérif, M., Duke, C., 2000. Adjustment procedures of a crop model to the site specific characteristics of soil and crop using remote sensing data assimilation. *Agric. Ecosyst. Environ*., 81, pp. 57–69.

Hamar, D., Ferencz, C., Lichtenberg, J., Tarcsai, G., and Frencz-A' rkos, I., 1996. Yield estimation for corn and wheat in the Hungarian Great Plain using Landsat MSS data. *International Journal of Remote Sensing*, 17, pp. 1689–1699.

Huang, Y.F., Li, Y.Z., Li, B.G. and Chen, D.L., 2001. Water and nitrogen optimal management under agricultural field of the north China Plain. *Transactions of the CSAE*, 17(2), pp. 37-41. (In Chinese)

Izaurralde, R.C., Rosenberg, N.J., Brown, R.A., Thomson, A.M., 2003. Integrated assessment of Hadley Centre climate change projections on water resources and agricultural productivity in the conterminous United States. II. Regional agricultural productivity in 2030 and 2095. *Agric. For. Meteor*., 117, pp. 97–122.

Maas, S.J., 1988. Use of remotely-sensed information in agricultural crop growth models. *Ecological Modelling*, 41, pp. 247-268.

Manjunath, K.R., Potdar, M.B., 2002. Large area operational wheat yield model development and validation based on spectral and meteorological data. *International Journal of Remote Sensing*, 23, pp. 3023-3038.

Moulin, S., Bondeau, A., and Dele'colle, R., 1998. Combining agricultural crop models and satellite observations from field to regional scales. *International Journal of Remote Sensing*, 19, pp. 1021-1036.

Myneni, R.B., Hoffman, S., et al., 2002. Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment,* 83, pp. 214–231.

Paul C. Doraiswamy, Sophie Moulin, Paul W. Cook, and Alan Stern, 2003. Crop yield assessment from remote sensing. *PE&RS*, 69, pp. 665-674.

Rasmussen, M.S., 1992. Assessment of millet yields and production in northern Burkina Faso using integrated NDVI from the AVHRR. *International Journal of Remote Sensing*, 13, pp. 3431-3442.

Reynolds, C.A., Yitayew, M., Slack, D.C., Hutchinson, C.F., Huete, A., Petersen, M.S., 2000. Estimating crop yields and production by integrating the FAO Crop Specific Water Balance model with real-time satellite data and ground-based ancillary data. *International Journal of Remote Sensing*, 21, pp. 3487-3508.

Tan, G., and Shibasaki, R., 2002. Monthly Climatologically Aided Global Interpolation of Weekly Air Temperature and Precipitation. *Theory Appl. of GIS, Japan,* 10(1), pp. 8–17.

Tan, G. and Shibasaki, R., 2003. Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. *Ecological Modelling*, 168, pp. 357-370.

Tian, Y., et al., 2004. Comparison of seasonal and spatial variations of leaf area index and fraction of absorbed photosynthetically active radiation from Moderate Resolution Imaging Spectroradiometer (MODIS) and Common Land Model. *J. Geophys. Res.,* 109, D01103

Scholes, R.J., Skole, D., Ingram, J.S., 1995. A global database of soil properties: proposal for implementation. IGBP-DIS Working Paper #10, University of Paris, France.

Sharpley, A.N., Williams, J.R., 1990. EPIC -- The Erosion Productivity Impact Calculator. 1. Model Documentation. U.S. Department of Agriculture, Technical Bulletin No. 1768.