Asia-Pacific
Economic Cooperation

The Application of Remote Sensing and GIS Technology on Crops Productivity

Proceedings of Workshop

Beijing, 30-31 July, 2012

The Application of Remote Sensing and GIS Technology on Crops Productivity

Proceedings of Workshop

Beijing, 30-31 July, 2012

HE Yingbin, CHEN Youqi and YAO Yanmin

APEC Agricultural Technical Cooperation Working Group
July, 2012

APEC Project No.: ATC 09/2011."Workshop on the Application of Remote Sensing and GIS Technology on Crop Productivity among APEC Economies"

Prepared By:

Institute of Agricultural Resources ＆ Regional Planning (IARRP)

Chinese Academy of Agricultural Sciences (CAAS)
12 Zhongguancun South Avenue, Haidian District, Beijing, China
Tel: (86)10-82109622-117 Fax: (86)10-82106225
Website:www.iarrp.cn

Produced for
Asia-Pacific Economic Cooperation Secretariat
35 Heng Mui Keng Terrace Singapore 119616
Tel:(65)6891-9600 Fax:(65)6891-9690
Email:info@apec.org Website:www.apec.org

APEC No: 212-AT-04.3 ISBN: 978-981-07-3888-4

EDITORIAL COMMITTEE

Preface

Agricultural sustainability and food security are the top priorities in all the APEC economies, whether developed or developing. Remote sensing and GIS technology are gaining importance as useful tools in promoting agricultural management and development and ensuring food security. At present, remote sensing and GIS technology has played a significant role in crop classification, yield assessment and crop forecasting. In recent years, with APEC members' rapid economic development and technology progress, academic circle has accumulated a lot of successful experiences and expertise on application of remote sensing and GIS on crops productivity, which needs a platform to communicate and share.

In accordance with the 2010 and 2011 Leaders Declarations and the outputs of a series of ATCWG Annual Meeting, and based on actual above-mentioned needs, the "Workshop on the Application of Remote Sensing and GIS Technology on Crops Productivity among APEC Economies" was held in 30-31 July, 2012, in Beijing. The workshop aims at ensuring participants to share experiences, expertise and lessons on the issues related to the application of remote sensing and GIS technology on crops productivity (especially food crops or specific priority crops, rice and wheat) and food security. Moreover, organizers expected to strengthen capacity building of applying GIS and remote sensing technology to monitor crops acreage, predict crops production, and assess crops growth suitability and develop recommendations on food security strategies for APEC economies to promote the health and safety of populations. Therefore, this paper collection and the workshop should be particularly valuable in the context of APEC priorities.

Participants were actively involved in workshop deliberations. Presentations, discussions and questions were closely concerned with crops acreage abstraction and crops cultivation structure analysis by remote sensing and GIS technology, monitoring on crops growth situation by remote sensing and GIS technology, prediction on crops production by remote sensing and GIS and technological extension and adaption among different APEC economies.

After the meeting, delegates realized to share expertise and advanced technologies on the application of remote sensing and GIS technology on crops productivity among APEC member economies. Through the discussion, the distinguished APEC economies strengthened cooperation and exchange of various outputs and knowledge on the application of remote sensing and GIS technology on crops productivity. Moreover, the participating experts agreed to further linkage and mechanisms of exchange of information in related field and to establish a research network to promote sustainable agriculture development in APEC economies.

As a part of the workshop achievements, this proceeding consists of 18 articles, of which some was not presented at the workshop but implemented by editorial committee.

The publication of this proceeding is encouraged and financially supported by APEC Secretariat, APEC BMC, projects of the Ministry of Science and Technology of China (2010DFB10030) and the National Natural Science Foundation of China (41001049). I truly express my sincere appreciation to staffs working for this workshop and all the contributors who helped publish this proceedings. I hope that various people in the field would review this proceedings and that it will contribute to the progress of land use sciences.

HE Yingbin

Sep., 2012

CATALOGUE

Status of the Application of Remote Sensing and GIS in Agricultural Monitoring in Australia

Lucy Randall
Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), Department of Agriculture, Fisheries and Forestry, Australia
Lucy.Randall@daff.gov.au

Earth observation, principally remote sensing, enables the development of methods for cost-efficient collection and use of agricultural and natural resources information, including mapping and monitoring changes in land use and land cover nationally.

Australia has a range of established systems to collect and analyse information on agriculture, some using remote sensing and GIS. At a national level, agricultural monitoring includes:

The agricultural census undertaken by the Australian Bureau of Statistics (ABS) every five years, with annual surveys of approximately 20 per cent of the farms in non-census years.

ABARES' farm surveys collect detailed financial information for around 2000 farms from the broadacre cropping, grazing and dairy industries.

ABARES' national scale land use map, a modelled product which uses coarse-scale satellite data (pixel size of $1.1km^2$), ABS Agricultural Census commodity statistics (for agricultural land uses) and pre-existing, finer resolution catchment scale land use data as inputs.

ABARES' coordination of catchment scale land use mapping with Australian states and territories based on land tenure and other types of land use data, interpretation of high resolution imagery and field mapping.

Geoscience Australia'S (GA) national land cover mapping using a classification of MODIS EVI data with time-series coefficients. GA and ABARES have jointly developed the Dynamic Land Cover dataset and a report discussing the methodology for development and potential applications (Lymburner et al. 2011).

Ground cover mapped nationally using Landsat TM and MODIS NBAR data [CSIRO, GA and Joint Remote Sensing Research Program (JRSRP)]

CSIRO's pasture growth and biomass for temperate and Mediterranean agricultural zones based on MODIS data.

The Australian Climate and Agricultural weekly report which provides land managers and policy makers with soil moisture, temperature and rainfall and commodity information in a single report.

Other environmental and climate observation systems with associated continuous data streams from space allow monitoring of land surface and forest cover. In addition, satellite data on climate variables such as ocean temperature, precipitation and soil moisture provide invaluable information for assessing the impact of climate on agriculture, including drought monitoring (Climate R^3 2011).

Recent ABARES activities relevant to the application of remote sensing and GIS in agricultural monitoring have included:

Attendance at the GEO Global Agricultural Monitoring (GEO GLAM) meeting on 22-23 September 2011 in Geneva.

Hosting of an international workshop in Canberra on 13–14 February 2012 to discuss the technical feasibility of developing an integrated crop forecasting system, with representatives from the Asia-Pacific region, other agricultural organisations and academic institutions. At this workshop, experts in remote sensing, plant growth modelling and forecasting, and decision-support tools discussed remote sensing applications for agricultural monitoring and forecasting.

Synthesising the outcomes of the integrated crop forecasting system workshop into a scoping paper (Nikolova et al. in prep). The paper presents the workshop discussions and recommendations on the feasibility of developing a national integrated crop forecasting system that will combine near real-time crop area estimates with near real-time yield predictions to produce more accurate production estimates.

Participation in the Asia-Pacific Regional Space Agency Forum Regional Readiness Review for Key Climate-Related Earth Observation Satellite Missions (APRSAF Climate R^3) Workshop on 24 May 2012 in Perth to discuss the opportunities for future application of space observations in agriculture.

REFERENCES

[1]Climate R3 (2011) APSRAF Regional readiness - review for key climate-related Earth Observation Satellite missions. Pilot Phase Workshop report, 18–20 July 2011 Sydney.http://www.space.gov.au/CLIMATER3/Pages/ClimateR3Workshop.aspx

[2]Lymburner, L., Tan, P., Mueller, N., Thackway, R., Lewis, A., Thankappan, M., Randall, L., Islam, A., Senarath, U.

2011, The National Dynamic Land Cover Dataset, Geoscience Australia, Symonston http://www.ga.gov.au/earth-observation/landcover.

[3]Nikolova, S., Bruce, S., Randall, L., Barrett, G., Nicholson, M. (in preparation) Integrated Crop Forecasting – Outcomes from a workshop on the integration of remote sensing data and crop models, ABARES (Technical report), Canberra, TBC 2012.

FURTHER INFORMATION

[1]Australian Agricultural Census http://www.abs.gov.au/agcensus2011

[2]ABARES' farm surveys http://www.daff.gov.au/abares/surveys

[3]National land use mapping http://adl.brs.gov.au/ anrdl/ metadata_files/pa_luav4g9abl07811a00.xml

[4]Catchment scale land use mapping http://adl.brs.gov.au/landuse/index.cfm?fa=main.reporting

[5]National Land cover mapping http://www.ga.gov.au/earth-observation/landcover.html

[6]Soil moisture www.eoc.csiro.au/awap/

Canadian Crop Yield Forecaster (CCYF) : a GIS and statistical integration of agro-climates and remote sensing information

Aston Chipanshi, Yinsuo Zhang, Nathaniel Newlands, Harvey Hill, David Zamar
The Science and Technology Branch of Agriculture and Agri-Food Canada
Harvey.Hill@agr.gc.ca

1 INTRODUCTION

Impacted by the variability of climate and other environmental and economic factors, the yields of major Canadian crops vary considerably from year to year. For example, the standard deviation of the spring wheat yield in the 40 Census Agricultural Regions (CARs) of the Canadian Prairies ranged from 16-31% of its historical mean during 1976-2011 (Map 1). Early and accurate estimates of regional crop yield are much sought after information by producers, grain traders, and the agricultural industry as a whole to assist their decision making and risk management. Traditionally, regional or national crop yield estimated are made by field or farmer surveys conducted during or after the crop growing season (e.g.USDA, 1999; Statistics Canada, 2012b). The survey method is resource and time consuming and reliable estimates are not normally available until long after the growing season. Recent research (e.g. Qian et al., 2009; Mkhabela et al., 2011; Bornn and Zidek, 2012) showed that estimations of crop yield in Canadian prairies are improved by the inclusion of agro-climatic indices or remote sensing Normalized Difference Vegetation Indices (NDVI) at certain periods of the growing season. Both agro-climatic and NDVI indices are readily available in near real time and relatively cost-effective, thus could be promising alternative crop yield predictors in supplement of the traditional survey method.

The Canadian Crop Yield Forecaster (CCYF) is a geographic information system (GIS) and statistical based modelling tool for crop yield forecasting and risk analysis. It uses both observed agro-climatic and NDVI indices prior the date of forecast and the statistically generated values of these variables from the forecast date to the end of the growing season. The programming language used for the statistical modelling is an open source software R (R Development Core Team, 2008). Spatial data processing and map generating are achieved using ArcGIS 10.1 (ESRI, 2010).

The ongoing development of CCYF has been led by the Agro-Climate, Geomatics and Earth Observations (ACGEO) Division, The Science and Technology Branch (STB) of Agriculture and Agri-Food Canada (AAFC). Collaborative partners include the Environmental Health group at the Lethbridge Research Centre (LRC), STB, AAFC, Agricultural Remote Sensing group at the Eastern Cereal and Oilseed Research Centre (ECORC), STB, AAFC, the Crop Condition Assessment Program (CCAP) at Statistics Canada (StatCan).

2 DATA AND METHODOLOGY

2.1 General model and data flow

The spatial working units of the current CCYF yield forecast model are the Census Agricultural Regions (CARs) that delineated by the 2006 Census of Agricultural data collection and dissemination activities (Statistics Canada, 2007). The pilot study region described in this paper encompasses the 40 CARs covering the Canadian Prairies (Map 1) which are spread across the agricultural regions of Alberta (CAR IDs 48xx), Saskatchewan (47XX) and Manitoba (46XX). The crop used to evaluate the CCYF methodology is spring wheat. The general data and model flow processes are illustrated in Figure 1.

Historical crop yield data from 1976-2011 for each of the 40 prairie CARs are obtained from the Field Crop Reporting Series of the Agriculture Division, Statistics Canada (Statistics Canada, 2012a).

The original images of the Advanced Very High Resolution Radiometer (AVHRR, ~1km resolution) NDVI are obtained by the National Oceanographic and Atmospheric Administration (NOAA) series of satellites (http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html) and the original images of MODerate-resolution Imaging Spectroradiometer (MODIS, 250m resolution) NDVI are obtained by the Terra and Aqua satellites of National Aeronautics and Space Administration (http://modis.gsfc.nasa.gov/data). The processing of the weekly NDVI composites is detailed in Reichert and Caissy (2002) and in Bédard et al. (2006). A cropland mask from Land Cover for Agricultural Regions of Canada (circa 2000) developed at AAFC is used to extract the NDVI values at pixels of cropland and make averages at CAR level. The AVHRR NDVI data used in this study are available from 1987 to Julian week 26 (last week of June) of 2012.

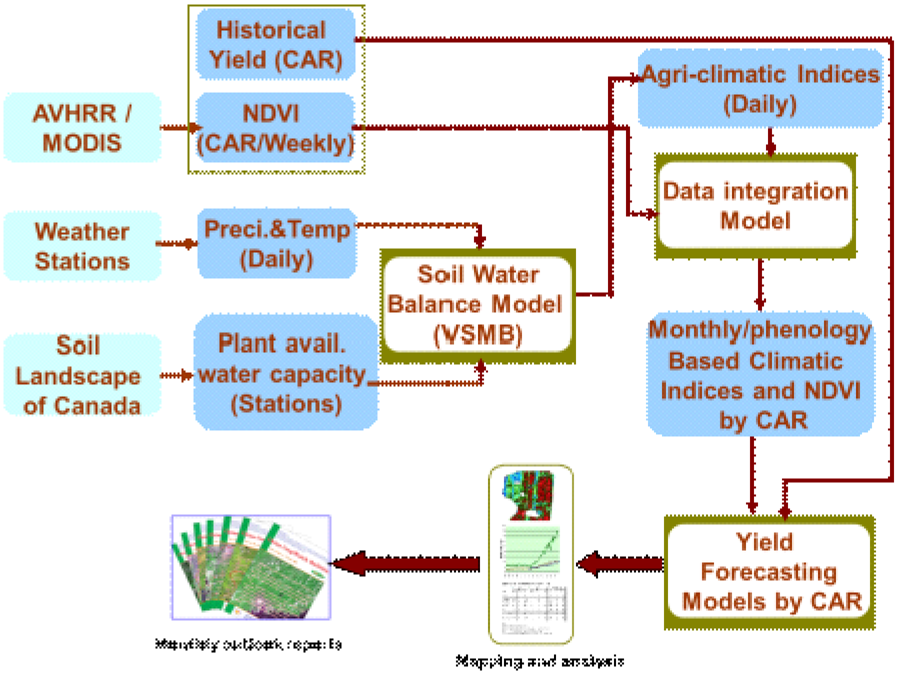


Figure 1: Model and data flow of Canadian Crop Yield Forecaster

The station based daily temperature and precipitation data are provided by Environment Canada and other partner institutions through a Drought Watch program (http://www.agr.gc.ca/pfra/drought/index_e.htm) operated at the National Agroclimate Information Service (NAIS) of AAFC. The data have gone through a quality control process and a gap-filling process to construct a continuous daily series from 1987 to June 2012, to be in line with the available NDVI data series. In total, 259 climate stations were selected in the prairies to represent the climate of the 40 CARs (Map 2). Only climate stations distributed in the cropland and has less than 10% of missing data are selected. Plant Available Soil Water Holding Capacity (PAWHC) at the location of a climate station is determined from soil data obtained from the Canadian Soil Information System (http://sis.agr.gc.ca/cansis). The station based temperature, precipitation and PAWHC are fed into a crop specific soil water balance model- Versatile Soil Moisture Budget (VSMB, Baier et al., 2000) to generate the agro-climatic indices used for the yield forecasting model. The agro-climatic indices used in current model include Growing Degree Days above 5 ^{0}C (GDD), precipitation (P), percent of PAWHC (%PAWHC) and a soil stress index (SI) defined as SI = 1 - AET/PET, where AET and PET are actual and potential evapotranspiration respectively. To represent the agro-climate of each CAR, average values of all the stations in the cropland of that CAR were calculated for all the agro-climatic indices. In certain CARs where there are very few stations selected or the stations are unevenly distributed within the cropland (e.g. 4751, 4780, 4781, 4790 etc. See Map 2), stations from neighboring CARs may also be used.

The daily agro-climatic indices are further aggregated into monthly means (or sums) and the weekly NDVI are aggregated into 3-week moving means to form the potential predictors for the crop yield. All model inputs include historical crop yield, NDVI and agro-climatic indices are then fed into a statistically based modelling frame work (Fig. 2) to generate the yield model for each CAR and make the forecasts using near-real time inputs. The outputs are further analyzed using ArcGIS (Version 10.1) to generate maps for the outlook reports.

2.2 Statistical processes

As illustrated in Figure 2, to generate the yield forecasting models that are customized to each CAR, the historical series of crop yield, NDVI and Agro-climatic predictors are first put into a Robust Least Angle Regression Scheme (RLARS) (Efron et al., 2004; Koller and Stahel, 2011) to evaluate and rank the correlations between the yield and each of the potential predictors. Once the maximum allowed predictors (currently set at 5) are selected for each CAR, a robust based Leave-One-Out-Cross- Validation (LOOCV) scheme is then implemented to finalize the predictors and parameters of the yield forecasting models. Bornn and Zidek (2012) have showed that incorporating spatial correlation into crop yield models could considerably increase the individual model's prediction power and stabilize the model performance. Therefore, we adopted

the Bayesian statistical scheme as described by Bornn and Zidek (2012) and use the historical data of the forecasting CAR and statistically selected neighboring CARs to establish the prior distribution of the predictors. The posterior distribution of the predictors is achieved using Markov Chain Monte Carlo (MCMC) scheme (Dowd, 2006; Martin and Quinn, 2007) fed by the prior distributions and the near real time data obtained at the time of forecasts. The predictors from the date of forecast to the end of growing season are established by a Multivariate Adaptive Regression Splines (MARS) using the posterior distribution obtained by MCMC.
The near real time data and the generated data are then fed into the yield forecasting model of each CAR to forecast the probability of yield distribution. The final output includes forecasted yield medians and their percentiles, such as 10% percentile (Worst 10%), 50% percentile (median) and 90% percentile (Best 10%).

2.3 Model evaluation

The performance of a model can be evaluated by their goodness of fitting between the predicted yields to the observed yields during the model calibration period and during the independent test period. One limitation is availability of NDVI inputs, only 25 years of recorded yield data is used in model evaluation of this study, data from 1987 to 2008 were used to build the forecast models, to calibrate the model coefficients (α0, α1… αn), and to test the back-fitting performance, while data from 2009-2011 was used to conduct independent model tests. Various performance indicators were suggested by model evaluation studies (e.g. Krause et al., 2005; Rahbeh et al., 2011; Szulczewski et al., 2012). The following indicators are some of the most commonly used indicators and should be sufficient to evaluate forecast capacity of the established model for each CAR.

(1)Bravais and Pearson Coefficient of determination (R^2)

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}} \right)^2 \qquad (1)$$

Where O is observed yield and P is predicted yield, bar values are their means. R^2 is the most frequently used model performance indicator. The range of R^2 lies between 0 and 1, which describes how much of the observed dispersion is explained by the predictions.

(2)Root Mean Square Error (RMSE)

RMSE has the same unit as the yield and is a good measure of absolute error.

$$RMSE = \sqrt{\sum_{i=1}^{n}(O_i - P_i)^2 / n} \qquad (2)$$

(3)Mean Absolute Percentage Error (MAPE)

$$MAPE = 100 \cdot \frac{1}{n} \cdot \sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \qquad (3)$$

3 EVALUATION RESULTS

3.1 Bravais and Pearson Coefficient of determination (R^2)

R^2 values are only evaluated during the model calibration period due to the sample size restriction during the model testing period. Map 3 shows that 31 out of the 40 prairie CARs (77.5%) achieved a R2 of larger than 0.5, which means on 77.5% CARs, more than half of the yield variance could be explained by the selected predictors. Of the 9 remaining CARs (red in Map 3) that have R2 smaller than 0.5, one is located in the province of Alberta (48XX), three in Saskatchewan (47XX) and five in Manitoba (46XX). Uneven or sparse distribution of climate stations and/or cropland in those CARs (Map 2) might be one of the reasons that caused the bad performance of those yield models.

3.2 Root Mean Square Error (RMSE)

The RMSE calculated during model calibration period (Map 4a) are generally smaller than those during model testing period (Map 4b), indicating that some yield impact factors might be missed during the model selection process. In general, the model predict the spring wheat yield reasonably well, 75% of the CARs achieved the RMSE of less than 6 bushels/acre during the three model testing years. Regionally, the forecast errors are smaller in Alberta than those in the other two provinces, most likely due to their densely and evenly distributed climate stations inside the CARs. Yield models in CARs that experienced large increases in the RMSE values from model calibration period to model testing period (e.g. CAR 4870, 4721, 4606 and 4611) require further investigation.

3.3 Mean Absolute Percentage Error (MAPE)

Similar to the trend of RMSE, the MAPE generally increased from the model calibration period (Map 5a) to the model testing period (Map 5b). The regional distribution pattern is also similar to the RMSE, i.e. forecasts in Alberta are better than those in Saskatchewan and Manitoba. During the three year model independent tests, the mean relative forecast error are within 10% in 17 CARs (42.5%), between 10-20% in 18 CARs (45%) and larger than 20% in 4 CARs (10%). The surveyed yields (observation) in all three testing years are missing in CAR 4604 which meant no error evaluation was done for this CAR.

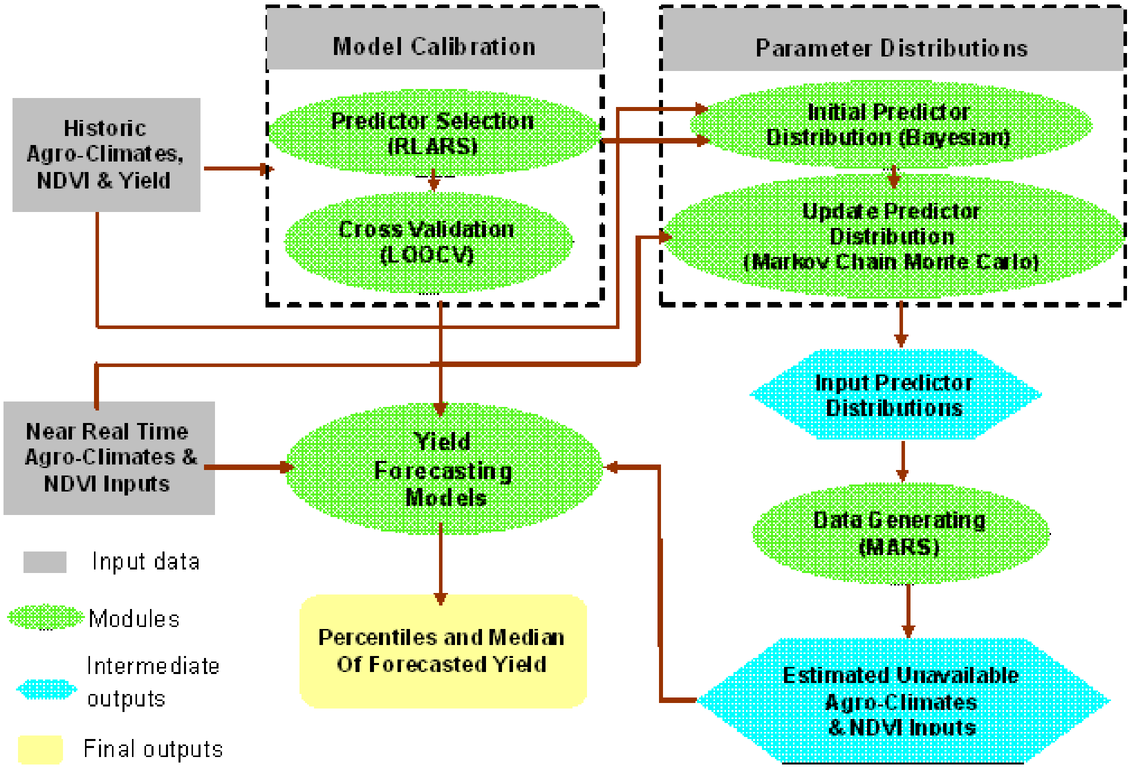


Figure 2: Statistical modelling frame work of the Canadian Crop Yield Forecaster

3.4 Model Effectiveness Index (MEI):

MEI is basically defined as a comparison between the mean forecasted errors with its historical yield variation. As showed in Map 6, during the model calibration period (Map 6a), only one CAR (4610) has a mean forecast error larger than the standard deviation of its historical yield. However, the number of CARs that were disqualified from being considered as valuable yield model s(MEI >100%) increased to seven during the three year model testing period (Map 6b), one is located in north-western Alberta, three in central eastern Saskatchewan and three in eastern Manitoba. Almost all of those bad performed CARs have unevenly or sparsely distributed climate stations and/or cropland (Map 2).

3.5 Model predictors

Model predictors are automatically selected by a statistical process as shown in Fig. 2. Based on the sample size for model calibration and some preliminary tests, a maximum of five predictors are allowed for each yield model, in addition to the technical trend in Eq. (1). Table 1 lists the top 10 predictors selected by the 40 models of Prairie CARs. The results showed that climate conditions in July and NDVI of Julian week 28 to 32 (Early July to Early August) are very critical for the spring wheat yield of many Prairie CARs. In addition to the predictors listed in table 1, some less frequently occurred predictors are distributed all across the growing season (May to September). Some of those selected predictors may need further investigation to find out the mechanisms as how they are related to the yield of that CAR (e.g., GDD or precipitation in September).

3.6 Forecast time and the regional forecast errors

As the CCYF frame work designed to deliver forecast during or shortly after the growing season, some of the predictors may not be available at early forecast date. In that case, a Markov Chain Monte Carlo (MCMC) scheme were used to generate a distribution of predictors based on the current year near real time data and prior distribution generated from historical data (Fig. 2). Figure 3 shows the evolution of forecasted percentile range and the comparison of the forecasted medians to the surveyed yield (observation) with the proceedings of the forecast dates. The temporal trend are very similar in all three provinces and the entire Prairies, the range of 10% and 90% percentiles reduced from June to August but remained fairly steady after August's forecasts, indicating that the conditions before the end of July are the most important factors determines the regional spring wheat yield of the Prairies. Among the three provinces during the three testing years, Alberta achieved the most reliable regional yield forecasts while Manitoba largely overestimated the yield. The MAPEs of

Alberta forecasts made on or after August during the three tested years were all within 3%, and the MAPEs of Saskatchewan made on or after August were within 12%. The MAPEs of Manitoba made on or after August in 2009, 2010 and 2011 were 4%, 10% and 20% respectively. The success in Alberta could partly attribute to the good representation of climate stations in their cropland while the failure in Manitoba of 2011 were most likely caused by the models' failure to properly reflect an extensive flood that occurred in its main agricultural region.

Table 1: Top 10 yield predictors selected in the Prairie CARs

Rank	Predictors	# Occurrence
1	SI of July	11
2	GDD of July	10
3	Precipitation of July	9
3	NDVI of Week 29-31	9
5	NDVI of Week 30-32	8
6	GDD of June	6
6	NDVI of Week 28-30	6
6	NDVI of Week 18-20	6
9	GDD of August	5
9	%_PAWHC of July	5

4 EXPERIMENTAL FORECASTS AND FUTURE DEVELOPMENT

4.1 Delivery of the experimental forecasts

Based on the above model evaluation results, the first operational prototype Prairie Spring Wheat yield outlook report was produced in June 2012. This experimental product has been updated monthly throughout the 2012 growing season with a release date normally a two to three week lag from the last day of the actual input data observed, i.e. a forecast released on the mid-July would use observed agro-climates and NDVI data until the end of June. Four deliveries are planned for 2012 from June to September. The report includes maps showing the forecasted median yield of the 40 Prairie CARs and their departure from the last five year's median of the surveyed yields. The forecasted 10 and 90 percentiles (best 10% and worst 10%) and median values of total production for three provinces and total prairie are also reported using estimated seeding area from the field crop reporting series of Statistics Canada (2012b) released on June. Some reference maps and figures, such as Maps 2 and 6b and figure 3 are also included in the report as appendices to help the user better understanding the forecasts and the expected confidence level.

4.2 Future Development

4.2.1 Improve the yield forecasting models on problematic CARs.

As revealed in the model evaluation, some CARs (e.g. the CARs in red color in map. 3 and 6b) did not achieved satisfactory yield model, further investigation is required. Some potential measures to be explored include: (1) to improve the climate data representation in those CARs by bringing more stations from other sources or using gridded climate datasets, (2) to consult with crop experts to bring in physically based indicators, (3) to explore the yield predictability of other available earth observation data, e.g., Enhanced Vegetation Index (EVI) and surface soil moisture obtained from Soil Moisture Active/Passive satellites (SMAP) etc.

4.2.2 Expand the products to other crops and other regions

Works are ongoing to build models and test their performances for other crops in addition to the spring wheat and other CARs outside the Canadian Prairie.

4.4.3 Refine the spatial resolution of the forecast units

The Census Agricultural Region (CAR) is used as the forecast unit is due to the fact that the source of historic yield data is Statistics Canada which reports yields by this unit. The boundaries of CARs are largely administrative rather than environmentally or ecologically based. It is recognized by many crop experts that the aggregation of information in CARs masked some of the correlations between crop yields and environmental based predictors. Efforts from both AAFC and Statistics Canada are being made to develop yield products in smaller and ecological boundary based spatial units. Once those products become available, it will be possible for us to develop yield models in refined spatial units.

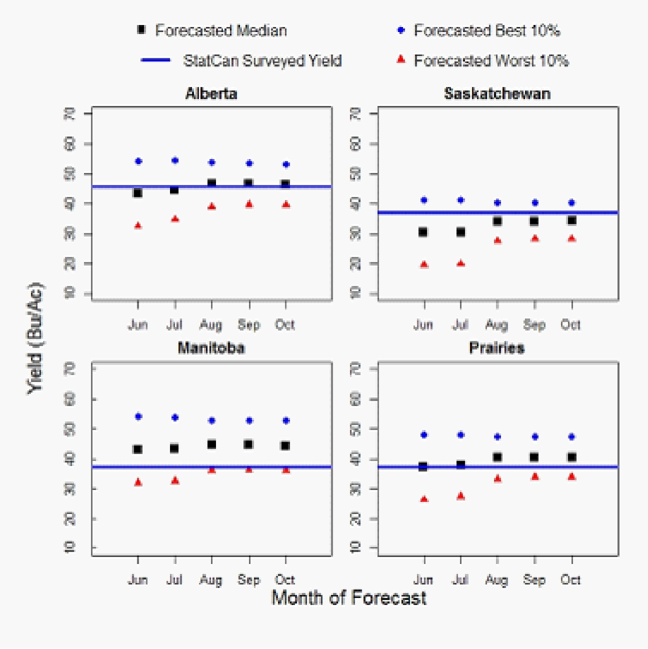


Figure 3: The evolution of the forecasted interquartile range and the departure of the forecasted median to the surveyed yield for the spring wheat of the three Prairie Provinces and for the entire Prairies during the three model testing years (2009-2011).

ACKNOWLEDGEMENTS

This study was supported by two AAFC funded projects (1) Climate Adaptation for Resilience in Agriculture (CARA) and (2) the Sustainable Agriculture Environmental Systems (SAGES) -Integrated Earth Observation Information on Crops and Soils for Agri-Environmental Monitoring in Canada. Some of the data used in this study are provided by partners in Statistics Canada and Environment Canada. The authors would like to thank C. Champagne, P. Cherneski, B. Daneshfar, A. Davidson, X. Geng, E. Gorelov, A. Howard, I. Jarvis, D. Qi, B. Qian, R. Rieger, L. Townley-Smith, D. Waldner and R.T. Warren From AAFC and F. Bedard and G. Reichert from Statistics Canada for their support and contributions.

REFERENCES

[1]Bédard, F., Crump, S. , Gaudreau, J. , 2006. A comparison between Terra MODIS and NOAA AVHRR NDVI satellite image composites for the monitoring of natural grassland conditions in Alberta. Canada, Can. J. Remote Sensing, 32 (1), 44–50.

[2] Bornn, L. and Zidek, J. V., 2012. Efficient stabilization of crop yield prediction in the Canadian Prairies, Agricultural and Forest Meteorology, 152, 223-232.

[3] Dowd, M., 2006. A sequential Monte Carlo approach for marine ecological prediction. Environmetrics, 17: 435–455.

[4] Efron, B., Hastie, T., Johnstone, I.., Tibshirani, R. 2004. Least Angle Regression, Annals of Statistics , 32 (2), 407–499.

[5] ESRI, 2010. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute. URL: http://www.esri.com/

[6] Friedman, J., 1991. Multivariate Adaptive Regression Splines (with discussion) Annals of Statistics 19 (1), 1–141

[7] Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction (2nd Ed.), Springer, pp 219-259. URL:http://www.stat.stanford.edu/~tibs/ElemStatLearn/,

[8] Koller, M. and Stahel, W. A., 2011. Sharpening Wald-type inference in robust regression for small samples, Computational Statistics & Data Analysis 55(8), 2504–2515.

[9] Krause, P., Boyle, D. P., Base, F., 2005. Comparison of different efficiency criteria for hydrological model assessment, Advances in Geosciences, 5, 89–97.

[10]Martin, A. D., Quinn, K.,M., 2007. MCMCpack: Markov chain Monte Carlo (MCMC) Package, R package version 0.8-1, URL: http://mcmcpack.wustl.edu.

[11]Mkhabela, M. S., Bullock, Paul, Raj, S., Wang, S., Yang, Y, 2011. Crop yield forecasting on the Canadian Prairies using MODIS NDVI data, 151, 385–393.

[12]Qian, B., De Jong, R., Warren, R., Chipanshi, A., Hill, H., 2009. Statistical spring wheat yield forecasting for the Canadian Prairie provinces. Agr. Forest Meteorol. 149, 1022–1031.

[13]R Development Core Team, 2008. R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

[14]Rahbeh, M., Chanasyk, D., Miller, J., 2011. Two-Way calibration-validation of SWAT model for a small prairie watershed with short observed record, Canadian Water Resources Journal, 36(3): 247-270.

[15]Reichert, G.,C., Caissy, D., 2002. A Reliable Crop Condition Assessment Program (CCAP) Incorporating

NOAA AVHRR Data, a Geographical Information System, and the Internet. In, Statistics Canada. Ottawa,On. URL: http://www26.statcan.ca/ccap-peec/esri2002conf-eng.jsp

[16]Statistics Canada, 2007. Census Agricultural Regions Boundary Files for the 2006 Census of Agriculture - Reference Guide. URL:http://www.statcan.gc.ca/bsolc/olc-cel/olc-cel?lang=eng&catno=92-174-G.

[17]Statistics Canada, 2012a. 1976-2011 Crops Small Area Data, Field Crop Reporting Series of Agriculture Division, Statistics Canada.

[18]Statistics Canada, 2012b. Definitions, data sources and methods of Field Crop Reporting Series, Record number: 3401, Agriculture Division, Statistics Canada. URL:http:// www.statcan.gc.ca/imdb-bmdi/3401-eng.htm

[19]Szulczewski, W., Zyromski, A., Biniak-Pieróg, M., 2012. New approach in modeling spring wheat yielding based on dry periods, Agricultural Water Management, 103, 105– 113

[20]USDA, 1999. Understanding USDA Crop Forecasts, National Agricultural Statistics Service and Office of the Chief Economist, World Agricultural Outlook Board, United States Department of Agriculture, Miscellaneous Publication No. 1554. URL:http://www.nass.usda.gov/Education_and_Outreach/Understanding_Statistics/pub1554.pdf

Supporting Agricultural Monitoring in APEC with FengYun Satellite Data

Jinlong Fan[1] and Mingwei Zhang[1]

National Satellite Meteorological Center, China Meteorological Administration, Beijing 100081

fanjl@cma.gov.cn

***Abstract*—With 40-year development, the Chinese Meteorological Satellite system has made great progress and is becoming a significant component of the Global Earth Observation System of Systems. The National Satellite Meteorological Center (NSMC) of China Meteorological Administration (CMA) is in charge of the development of the Chinese Meteorological Satellite which is also called FengYun satellite in Chinese. The Chinese Meteorological Satellite system has put in place two series, polar-orbiting satellite and geostationary satellite. Since 2008, FY-3A and Fy-3B have been successfully launched respectively. Two sensors onboard FY-3A and FY-3B, VIRR and MERSI are very important for the agricultural monitoring and with the similar observing capabilities as NOAA/AVHRR and EOS/MODIS or ENVISAT/MERIS. NSMC has developed a web based data distribution system through which users may get access to the satellite data that NSMC receives. CMA also developed a communication satellite based data distribution system, CMACast, upgraded from the FENGYUNCast that NSMC developed in 2005, to distribute larger volume satellite data to the end users in near and real time. CMACast has joined the GEONETCast as a regional hub in Asia and Pacific area. CMA has donated the CMACast user stations to the international users in 2006, 2007 and 2011, in order to facilities the users in Asia and Pacific to receive the satellite data. New donation plans to users in other communities, such ESCAP space community and APEC Agricultural monitoring community, are being initiated. It hopes that these donations may help more alien users in Asia and Pacific easily get access to Chinese satellite and other satellite data. In terms of the agricultural monitoring, some similar satellite products that NSMC is operationally producing may be transferred to the agricultural monitoring community in APEC. Those products are vegetation growth monitoring, vegetation drought monitoring and land surface temperature monitoring. It hopes that users in Asia and Pacific area may benefit from the utilization of the Chinese Fengyun Satellite data to monitoring their own agriculture.**

Keywords*— Fengyun Satellite; Agricultural Monitoring; APEC, GEONETCast; CMACast

The 21st century is a new era when it is a global boomingly age for Earth observations. In recent years, a great progress has been made in space based Earth Observations system in China. Chinese satellites series, for instance ‘FengYun’ meteorological satellite series, has developed and is developing. With 40-year development, the Chinese Meteorological Satellite system is becoming a significant component of the Global Earth Observation System of Systems. The National Satellite Meteorological Center (NSMC) of China Meteorological Administration (CMA) is in charge of the development of the Chinese Meteorological Satellite which is also called FengYun satellite in Chinese. The Chinese Meteorological Satellite system has put in place two series, polar-orbiting satellite and geostationary satellite. However, CMA also has paid great attentions to the satellite data distribution and applications in home and abroad. NSMC has developed a web based data distribution system through which users may get access to the satellite data that NSMC receives. CMA also developed a communication satellite based data distribution system, CMACast, to improve the data access. CMA has donated the CMACast user stations to the international users in 2006, 2007 and 2011, in order to facilities the users in Asia and Pacific to receive the satellite data. Since 2008, FY-3A and Fy-3B have been successfully launched respectively. Two sensors onboard FY-3A and FY-3B, VIRR and MERSI are very important for the agricultural monitoring and with the similar observing capabilities as NOAA/AVHRR and EOS/MODIS or ENVISAT/MERIS. With those facilities in place, it sees that FengYun Satellite data may strongly support Agricultural Monitoring in APEC in the near future. This paper introduces the Chinese Meteorological Satellite program, the FengYun satellite data distribution, and the potential supports to the agriculture monitoring in APEC.

1. CHINESE METEOROLOGICAL SATELLITES PROGRAM

In 1971, The National Satellite Meteorological Center (NSMC) was founded to carry out the Chinese Meteorological Satellite Program. At present, NSMC is one of key operational centers in the China Meteorological Administration (CMA). The NSMC’S mission is to plan, develop and operating the Chinese meteorological satellite system and to promote the satellite application in the relevant areas. After 40-year development, the NSMC composes of one operational center and four ground stations in China. With the needs of receiving global data, NSMC has negotiated with Swedish Space Company and reached an agreement of renting the facility in Kiruna ground station to receive and send FY3 satellite data back to NSMC.

At the early 1970s, China began to independently develop its meteorological satellite. Two major series, the polar-orbiting and the geostationary meteorological satellite systems, were planed, designed and developed in the past 40 years. The first polar orbiting experimental meteorological satellite (FY-1A) was successfully launched in late 1980s. In recent years, aiming at meeting the increasing demands of economy and society, China has launched its second generation polar orbiting meteorological satellites, FY-3A and FY-3B in 2008 and 2010, respectively. FY-3A and FY-3B both carry 11 payloads of which VIRR, the short name for Visible Infrared Scanning Radiometer, and MERSI, the short name for Medium Resolution Spectral Imager, are both key valuable sensors for the agriculture monitoring. VIRR data are 1.1 km resolution of 10 channels while MERSI data are 250 meter resolution of 5 channels and 1 km of 15 channels. The FengYun satellites are becoming more and more important in protecting lives and property of people from natural disasters.

The Chinese Meteorological Satellite was named as FengYun or FY in acronym, which means wind and cloud in English. The odd number series is the polar-orbiting satellite series, the even number series the geostationary.

FY-1 series is the first generation of FengYun polar-orbiting meteorological satellites. The FY-1 polar-orbiting, sun-synchronous meteorological satellite program has been implemented since 1988. 4 satellites, FY-1A/B/C/D were launched to provide visible and infrared radiometry measurement for the application. Satellite products include the vegetation index (NDVI), sea surface temperature (SST), atmospheric optical thickness and so on. FY-1D is the last model of the FY-1 series and was operationally active as of April 2012.

FY-2 series is the first generation of FengYun geostationary meteorological satellites. The FY-2 geostationary satellite program has produced 6 satellites, FY-2A/B/C/D/E/F since 1998. FY-2D at 86.5 E and FY-2E at 105E constitute a dual satellite constellation for operational observation. FY-2F was newly launched in Jan. 13 2012. FY-2 satellites carry the Visible and Infrared Spin Scan Radiometer with 5 spectral observational channels.

FY-3 series is the second generation of FengYun polar-orbiting meteorological satellites. The FY-3 is a new polar-orbiting, sun-synchronous meteorological satellite series planned to cover the duration of 2008-2021. The first model FY-3A was launched in May 2008. The second model FY-3B was launched in Nov. 2010. Compared with the visible and infrared imagery of FY-1 satellite, the FY-3 satellite carries 11 sensors which largely enhance the monitoring capability.

FY-4 series is the second generation of FengYun geostationary meteorological satellites. The FY-4 is a new geostationary meteorological satellite series plans to cover the duration of 2016-2020. Compared with FY-2 satellites, FY-4 is capable of infrared hyper-spectral resolution atmospheric vertical sounding of temperature, humidity, and greenhouse gases. The spatial resolution of imagery is improved to 100 meters.

Since early 1980s, the polar orbiting and geostationary meteorological satellite data have been applied widely to many fields like weather forecasting, climate prediction, natural disaster monitoring, crop production estimation, environmental monitoring and space weather, etc. Fig. 1 shows the global observing capability of FY-1C. FY-1D, FY-3A and FY-3B all have this capability.

2. FENGYUN METEOROLOGICAL SATELLITE DATA SERVICES

Since the early 1980s, National Satellite Meteorological Center (NSMC) has been receiving, processing and archiving data from alien meteorological satellites and Chinese Meteorological satellites. So far, NSMC has become one of the largest satellite data centers in China, even in the world. In order to easily provide the huge volume archived and received satellite data, a web based satellite data service was developed under the support of the FengYun Meteorological Satellite Ground Application System Project. Since 2005, the domestic and foreign users have been able to access to the FengYun Satellite data at http://satellite.cma.gov.cn. Fig.2 shows the portal of the FengYun satellite data services. The portal provides the users with real-time and historical satellite data that were acquired and are acquiring from the FY-1D, FY-3A, FY-3B, FY-2D, FY-2E, NOAA-15, NOAA-16, NOAA-17, NOAA-18, EOS/TERRA, EOS/AQUA, MTSAT-2, MSG-1 and so on.

In order to meet the special users' needs, the communication satellite based data dissemination service is also available, which complements to the web based data distribution service. FENGYUNCast was developed in 2005 in NSMC to disseminate satellite data that NSMC receives. And later on FENGYUNCast joined the GEONETCast as a regional hub for the Asia and Pacific area.

GEONETCast is a low cost global environmental information delivery system which transmits the satellite-based, airborne-based and in situ data, products and services from the Global Earth Observation System of Systems (GEOSS) to various users through communication satellites using multi-cast, broadband capability. GEONETCast provides reliable, worldwide and continuous access to information and is a core infrastructure and early success of the Group on Earth Observations (GEO)'s the Global Earth Observation System of Systems (GEOSS). GEONETCast is coordinated within the framework of the GEO by the GEONETCast Implementation Group comprising the China Meteorological Administration (CMA), European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT), the National Oceanic and Atmospheric Administration (NOAA) and the World Meteorological Organization (WMO). Data from each region can be disseminated outside the original region through data-exchange links between regions, such as through dedicated lines, overlapping satellite footprints, or use of the Internet or other existing networks. The data GEONETCast delivers are specifically targeted to address nine society benefit areas such as natural and human-induced hazards, environment and health, environmental-related energy issues, climate change, water management, weather, ecosystem management, sustainable agriculture, and desertification and biodiversity, with the aim at reaching a global coverage and allowing the timely reception of the data at very low cost by nearly anyone on the planet.

The CMACast is upgraded from FENGYUNCast and enhanced by CMA in the support of the meteorological operation. CMACast is a newly established DVB-S2 standard satellite data broadcast system. It is maintained by the National Meteorological Information Center of CMA and works as a major component of CMA's national meteorological data dissemination system. More than 2400 subordinated agencies and local offices of CMA use this system to receive real time observation data and products. It is also the most effective way for common user communities in China to obtain different kinds of meteorological data and products from CMA. CMACast has achieved the ability to offer all services within the framework of GEONETCast and may provide much better services to users in Asia Pacific Region. Fig.3 shows the footprint of CMACast, within which user may use the service that CMACast provides.

In order to share data of FengYun meteorological satellite series with countries in the Asia-Pacific region, China has donated a number of user receiving equipments to users in the Asia-Pacific region. The China Meteorological Administration, on behalf of the Chinese government, ever donated six sets of FENGYUNCast user receiving stations to Bangladesh, Indonesia, Iran, Mongolia, Pakistan and Thailand in 2006 in the framework of the Asia Pacific Space Cooperation Organization. In October 2007, another 11 sets of FENGYUNCast user receiving stations were donated to DPRK, Kyrghyz, Lao P.D.R, Malaysia, Myanmar, Nepal, Philippines, Sri Lanka, Tajikistan, Uzbekistan and Viet Nam in the Framework of Group on Earth Observations. Fig. 4 shows the donation of CMACast user stations in 2007. China Meteorological Administration (CMA) donated CMACast and Meteorological Information Comprehensive Analysis and Process System (MICAPS) to the Asian developing countries at the 40th China Study Tour and Regional WIS Training Seminar opened on 11 April 2011 in Beijing in the framework of WMO. These countries are Thailand, Indonesia, Pakistan, Bangladesh, Philippines, Tajikistan, Sri Lanka, Mongolia, Viet Nam, Malaysia, Kyrgyz, Nepal, Myanmar, Maldives, Lao P.D.R and Uzbekistan. At present, there are 27 user stations in 19 counties in the Asia-Pacific region that are able to receive Earth observation data through the CMACast.

3. POTENTIAL SUPPORTS TO THE AGRICULTURAL MONITORING IN APEC

FengYun satellites are designed for the weather forecast but they have been used in many other fields. Agricultural monitoring is one of key application areas. FY-3A and FY-3B were launched in 2008 and 2010, respectively. FY-3A and FY-3B both carry 11 payloads of which VIRR and MERSI are both key valuable sensors for the agriculture monitoring. They have the similar observing capabilities as the NOAA/AVHRR and EOS/MODIS or ENVISAT/MERIS.

NSMC is operationally providing the vegetation growth monitoring, the vegetation drought monitoring and the land surface temperature monitoring in China. With the increasing needs of agricultural monitoring in APEC, these applications may be transferred to the APEC area. Of course, the users may be able to use FengYun satellite data to develop their motheds for the agricultural montiroing. It hopes that users in Asia and Pacific area may benefit from the utilization of the Chinese Fengyun Satellite data to monitoring their own agriculture. Fig.5 showcases the vegetation monitoring, drought monitoring and land surface temperature monitoring with FengYun polar-orbiting and geostationary satellite data.

The upper left picture is the vegetation growth monitoring. The upper right picture is the drought monitoring. The lower left picture is the land surface monitoring with FY Geostationary satellite data. The lower right picture is the number of days with higher temperature.

4. CONCLUSIONS AND RECOMMENDATIONS

The Chinese Meteorological Satellite system is becoming a significant component of the Global Earth Observation System of Systems. The Chinese Meteorological Satellite system has put in place two satellite series, polar-orbiting satellite and geostationary satellite. The users, including domestic and international, may get access to the Chinese meteorological satellite data through NSMC's satellite data services website. The users also may get access to satellite data through CMACast but users are needed to equip the CMACast user station that is inexpensive, small and easily manage. APEC agriculture monitoring community should be equipped with the CMACast user station to facilitate timely access to the satellite data for the operational agriculture monitoring. APEC trust fund and other stakeholders should take this requirement into consideration. The vegetation growth monitoring, vegetation drought monitoring and land surface temperature monitoring that are being done in NSMC showcase the potential supports to the agriculture monitoring in APEC. Two sensors onboard FY-3A and FY-3B, VIRR and MERSI are very important for the agricultural monitoring with the similar observing capabilities as the NOAA/AVHRR and EOS/MODIS or ENVISAT/MERIS.

ACKNOWLEDGEMENTS

The research is funded jointly by the National High Technology program with the grant of 2012AA12A307 and the International Scientific Cooperation program with the grant of 2012DFG21710.

5. REFERENCES

[1]Dong,C. H., Yang,J., Lu,N. M., Yang,Z. D., Shi,J. M., Zhang,P., Liu,Y. J., Cai,B., 2010. Main characteristics and primary applications of Polar-orbiting satellite FY-3A[J].Journal of Geo-information Science, 12(4): 458-465 (in Chinese)

[2]Fan,J. L., 2012. Progrss of the global environmental information dissemination services-GEONETCast[J]. Advances in Earth Science, 27(7):712-716(in Chinese)

[3]Fan,T. X., FY-1, 1991. Meteorological satellite ground system[J]. Chinese Space Sci Tech, 2:34-48 (in Chinese)

[4]Qian,J. M., Sun,A. L., Xu,Z., 2012. Fengyun series meteorological satellite data archiving and service system[J].Journal of applied meteorological science, 23(3) : 369-376(in Chinese)

[5]Yang,J., Dong,C. H., Lu,N. M., Yang,Z. D., Shi,J. M., Zhang,P., Liu,Y. J., Cai, B., 2009. FY-3A: the new generation polar-orbiting meteorological satellite of China[J].Acta Meteorological Sinica, 67(4):501-509(in Chinese).

Design of a Decision Support System for Suitability Regionalization of Conservation Tillage Based on GIS

Jiao Weihua[1], He Yingbin[2]
1. China Agriculture University; 2. Institute of Agricultural Resources and Regional Planning, CAAS
fanjl@cma.gov.cn

***Abstract*—Conservation tillage cannot be applied on a large scale on account of the variety of the region and the technology type in China. In order to overcome this problem, a decision support system for suitability regionalization of no-tillage, which belongs to conservation tillage, based on GIS was developed in this paper. On the basis of AHP and cluster analysis, we firstly built the suitability regionalization index of no-tillage, then calculated the weight of each index, and lastly developed the decision support system for suitability regionalization of no-tillage. In this paper, both the methodology on suitability regionalization and the decision support system have some reference for spreading no-tillage in the northern part of Yinshan mountain.**
Keywords — Conservation tillage; No-tillage; Suitability regionalization; GIS; Decision support system

1 INTRODUCTION

Currently, conservation tillage has become an important technical means to prevent soil erosions and reduce land desertification(Uri et al, 1998; Gao et al,2003). It also is one of the important supports for sustainable development of international agriculture technology. However, this kind of technology has lots of types and be scattered, with a little normative. This limits the conservation tillage's promotion and application. So it is very urgent to based on different regions' natural, social and economic conditions to research the space adaptive and layout of different technologies(Jiao et al, 2010).
GIS has unique advantages in the application of the zoning areas. It can combine the existing resources and economic database, the analysis bases on the physical and chemical properties, climatic factors, cultural, economic and many other factors of the minimum system unit, in the end it makes out a variety of regionalization(de Paz ea al, 2006).

In this paper, based on the analysis of intrinsically link between the conservation tillage (no-tillage for example), natural environment and socio-economic environment, the study of spatial distribution characteristics of the area of no-tillage technology, and the collecting expert opinions, the application of GIS technology has developed the Technical suitability zoning decision support system. The system can provide divisions of the suitability of different parts' no-tillage technology with the indicators provided by users. The aim is that to provide scientific methods and decision support for reasonable promotion of no-tillage in everywhere.

2 SYSTEM DESIGN

1.1 Design Target

Firstly, we build the suitability regionalization of no-tillage index system on the basic of AHP, then we use the index from users to analyse and evaluate the suitability of the selected area by way of GIS technology, aiming at separating the different suitability regionalization of no-tillage technology from each other and reasonably extend the no-tillage using scientific method and decision support system.

1.2 function module design

The system include five functional modules (as shown in Fig.1):(1) Knowledge View, introducing the technologies and effects of the conservation tillage. (2) Regionalization Results Query, the nucleus module that receiving the input index from users and dividing the different suitability regionalization. (4) User Login. (5) System Management, won't go into detail because of it is similar with the routine information system.

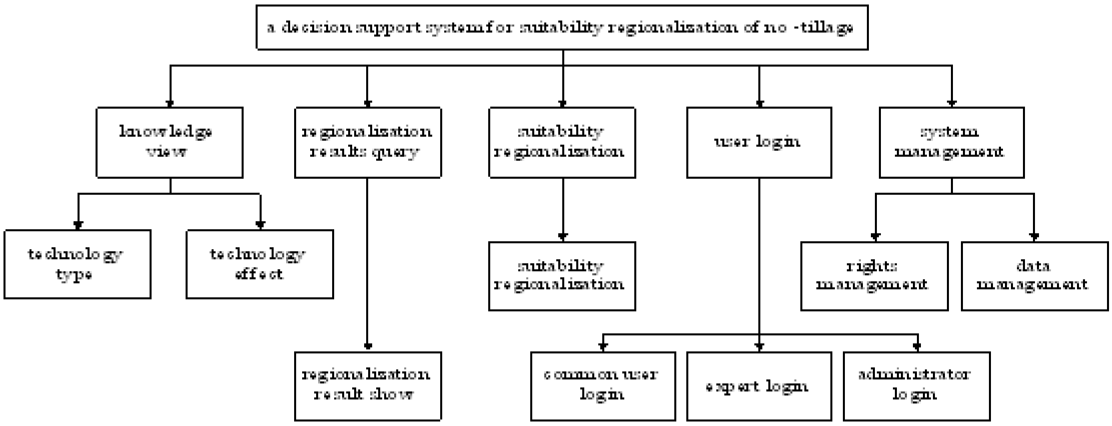


Fig.1 Function module structure of the system

1.3 structure of index

This article build the index system on the basis of the following principles:(1) Relative Consistency principle. (2) Comprehensive principle and Dominant factor principle. (3) Reginal Conjugatio principle. (4)Combination of qualitative and quantitative analysis principle. (5) integrity of the principle of administrative divisions(Chen et al,2002; Chen et al,2006).We screen and classify the suitability regionalization of no-tillage index into two kinds ,18 different index on the basis of experts' advice and refer to the above regionalization principle, as is shown on table 1. The D1—D7 are indirect pointer which is calculated from the original data. This system is a decision support system for the related agriculture department, and the users are assumed to have the ability to acquire the relevant data and calculate the system index. D8—D18 are direct index which can be obtained directly. This system regards both indirect index and direct index at as the input parameters.

1.4 confirmation the weight of index

There are many indexes in the division process of regionalization, but the regionalization of each index to evaluate the role of the object is not equally important. We must assign different weight coefficients to different index after the determination of index system, so as to reflect the different role and importance in the system of evaluation. The value of the index weight directly affects the result of regionalization, the variation of the weight will likely lead to the different quality of regionalization. This system calculates weight of index using the method of Analytical Hierarchy Process. The result is shown in Tab.1.

1.5 Cluster Analysis

In the field of environmental science, many different algorithmic Processes have been applied for Cluster Analysis, for example, System Clustering, Gradual decomposition clustering and Discriminant clustering. In this paper, shortest distance method is employed. Take the two point groups S and T for example, the shortest distance between S and T is used as the distance of them, And the shortest distance is defined as the criteria of judgment on types, presented as $dst = \min(dij, Pi \in S, Pj \in T)$.
SPSS(Statistical Package for the Social Science), which has a function of cluster analysis for the grid value in the preprocessing layers of planed regionalization regions , is embedded into the system. After obtaining the grid layers and weight which are all one-to-one correspondence with the indices, the system will have a overlying or weighting operation on all the quantified index layers, and will build a preprocessing layer of planed regionalization regions. Due to too much grid values, this system will divided the samples into 50 sample intervals and cluster them into 3 with the Cluster Analysis. The 3 clusters are suitability regions of no-tillage, subaltern suitability regions of no-tillage and unsuitability regions of no-tillage and they will be drew in a regionalization figure in the system .

2 SYSTEM IMPLEMENTATION

This decision support system utilizes GIS and Internet synthetically. Arcgis is selected to be the developmental tool and SQL Server2000 is selected to be the data base (Wang et al, 2008; Zhao et al, 2006). The interface for user login is shown in Fig.2. Suitability regionalization could be started after logging in (as shown in Fig.3).
Take the selection of soil indicator as the example, each index weight could be calculated in the index calculate interface(Fig.4)
Eventually, the result of division shows up, as is shown in Fig.5.

3 CONCLUSIONS

Conservation tillage cannot be applied on a large scale at the present stage in China. In order to solve this problem, a decision support system for suitability regionalization of no-tillage was designed. Based on AHP and cluster analysis, the suitability regionalization index of no-tillage is firstly build and then the index weight is calculated. And the decision support system was finally established with the help of functions of GIS in image display and cluster. It is considered that the decision support system is conductive to the spread of no-tillage in the northern part of Yinshan mountain.

Table 1 Index system for no-tillage zoning in the Wuchuan County

Overall Layer A	System Layer B	Index Layer C	Variable Layer D
Index System for no-tillage zoning	B1Natural System	C_1Soil Index	D_1soil organic matter
			D_2soil nitrogen
			D_3 soil total phosphorus
			D_4soil clay content
			D_5soil relative humidity
		C_2Topography Index	D_6slope
			D_7exposure
		C_3Land Use Status Index	D_8area of cultivated land per capita
			D_9 area of grassland area per sleep
			D_{10}woodland area proportion
	B_2Social Economy System	C_4Level of Mechanization Index	D_{11}agricultural machinery total power
			D_{12}sowed area ratio
		C_5Peasant Household Index	D_{13} acceptance level of no-tillage
			D_{14}agricultural workers proportion
			D_{15}farmland output-input ratio
			D_{16}number of livestock
		C_6Economics Index	D_{17}per capita gross output value of agriculture
			D_{18}per capita income

Figure 2. user login interface

Figure 3. index select interface

Figure 4. index calculate interface

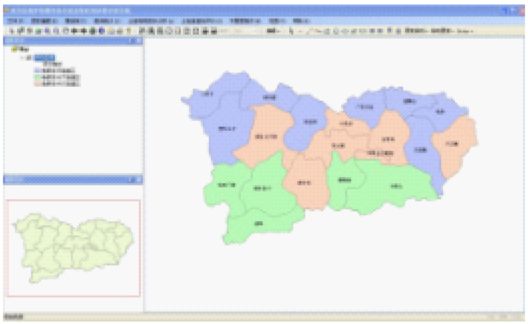


Figure 5.final suitability regionalization

ACKNOWLEDGEMENTS

This paper is funded by the National Natural Science Foundation of China (41001049); the Ministry of Science and Technology of China (2010DFB10030); the Key Program of National Natural Science Foundation of China (40930101); the National Basic Research Priorities Program of China (2007FY120100); the Commonweal Foundation of China's National Academy (201220229).

REFERENCES

[1]Chen, Z., Ma, S., 2006. Influential factors and control strategies of farming soil wind erosion in the corss region between farm land and grass land in Yinshan Mountain area[J]. Journal of Anhui Agricultural University, 33(1):130-133.

[2]Chen, Z., Wei, E. Shi, S., 2002. Strategies for rejuvenation of degenerated natural grassland within northern agro-grazing ecotone of yinshan mountains, Inner Mongolia[J].Research of Soil and Water Conservation, 3,9(1):41-45.

[3]De Paz, J. M., Sánchez, J., Visconti, F. , 2006. Combined use of GIS and environmental indicators for assessment of chemical, physical and biological soil degradation in a

Spanish Mediterranean region[J]. Journal of Environmental Management, 79: 150-162.

[4]Gao, H. Li, W.,Li, H., 2003. Conservation tillage technology with Chinese characteristrics[J].Transactions of the CSAE,19(3):1-4.

[5]Jiao, W.He, Y., Zhang, X. , 2010. Study on suitability regionalization of conservation Tillage Based on GIS[J].Transactions of the CSAE,41(2):47-51, 67.

[6]Uri, N.D., Atwood, J.D., Sanabria, J., 1998. The environmental benefits and costs of conservation tillage[J]. The Science of the Total Environment, 216:13-32.

[7]Wang, Z., Gan, G., Wang, J. , 2008. Crop growth simulation system based on web services and GIS and its application[J].Transactions of the CSAE, 24(1): 179-182.

[8]Zhao, P., Liu, G., Li, M. , 2006. Management information system for apple diseases and in sect pests based on GIS[J].Transactions of the CSAE, 22(12): 150-154.

Temporal and Spatial Variability of Soil Nutrients in the county scale of Fujian

KONG Qing-bo[1] , He Yingbin[2], ZHANG Ming-qing[1] Zhang Qing1 LI Juan[1]

1.Soil and Fertilizer Institute Fujian Academy of Agricultural Sciences , Fuzhou, 350013,China; 2. Institute of Agricultural Resources and Regional Planning, CAAS

kongqb@qq.com

***Abstract* - Based on the analysis of top soil sampling points , providing theoretic and Practice support for precision fertilization in the county scale of Fujian.. Temporal and spatial variability characteristics of farmland soil nutrient(SOM、alkali hydrolysable N、available P、available K)content were studied employing geostatistics statistics and geographic information system(GIS). Based on the analysis of top soil sampling points the county scale in space, The content of soil nutrient is big difference in different land; A contour map of nutrient content was obtained using ordinary Kriging interpolation, in accordance with soil fertility grades, spatial distribution information of alkali hydrolysable N were deficient in part of the regional, heavily deficient of available K and surplus of available P in Most of the regional respectively; for example, compared with 1980, it presents the uptrend of available P, also confirmed the accumulation of phosphorus in Nutrient balance.**

Keywords - Soil nutrient; Temporal and spatial variability; soil fertility grades

PREFACE

Soil is a natural Continuum, Spatial Variability is a natural essence of soil. It's a foundation to well manage the soil nutrient and properly implement the fertilization by getting a fully understanding of the spatial variability of the soil. Studies have proved that the soil nutrient is connected with the space, whose variability is different from Nutrient type, soil parent material [2,3], topography [4-8], human activities[9-11] etc. With the difference within A few meters, a few hundred meters, a few kilometers or even hundreds of kilometers, and through using the Kriging technic to analyze the soil nutrient spatial distribution pattern enable the achievement of many significant results.

Since the 1980s after the second soil census, the big differences between the Land use, cropping systems, tillage practices, fertilization levels have made a big influence on the variation of the soil nutrient. The original nutrient spatial distribution can no longer meet current production needs, the preparation of knowing the nutrient spatial variability has made to the application of the recommended fertilizer technique. Therefore, it's a great necessary to analyze the soil nutrient spatial variability of a larger scope, disclosing the characteristics of the soil nutrient spatial variability. At present, the studies of small spatial scales on the area of region or village have been made, but less on the county scale. Bases its analysis on the arable lands of the County regions of Southeast China, analyzing the spatial variation of soil nutrient, this article has an important reference value for guiding the county fertility and nutrient management.

1 MATERIAL AND METHOD

1.1 The basic situation of the study area

Choosing Jingjiang city and Minhou county as the study area. Its geographical location are located between east longitude 118 ° 51 ' to 119 ° 25' ,north latitude 25 ° 47 'to 26 ° 37 ' and east longitude 118 ° 24 ' to 118 ° 43', north latitude 24 ° 30 ' to 24 ° 54'. Lying in the central south and north counties of Fujian Province. Most of its terrain and Geomorphology are hills and alluvial plains. With the subtropical humid monsoon climate, its average annual precipitation is more than 1500 mm.

1.2 Sample collection and analysis

Firstly, the study was planned in the indoor, then setting GPS positioning in the field, analyzing the farmland soil of Jinjiang City and Minhou County by fixed-point sampling, to find the exact position of the sample. Fig. 1 has the distribution. The sampling depth is 0-20 cm, the sampling time is late March 2007 to early April. The selected soil nutrient indicators include soil organic matter, available nitrogen, rapid available phosphorus, rapid available potassium, applying potassium dichromate volumetric method to test soil organic matter and using Olson to test rapid available phosphorus. The rapid available potassium adopted NH4Ac to extract, and flame photometry to test and Available nitrogen can be tested by alkaline hydrolysis diffusion method[18].

1.3 Spatial Analysis

To calculate the variograms of soil nutrient values by using of geostatistics components in GS +5.1, and involving the geostatistical semi variance. Using the ordinary Kriging interpolation to obtain the main nutrient indexes by respectively using ArcGIS9.0 and fitting them to the contour map based on the parameter values of the variogram[19].

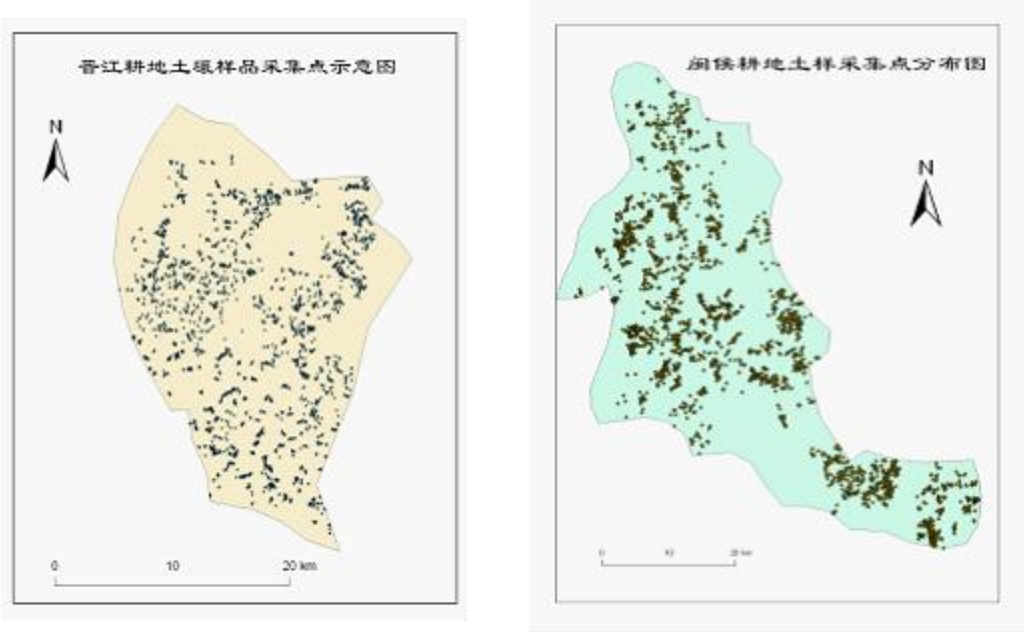


Fig. 1　Location of study region and sample site distribution

2 RESULT AND DISCUSSION

The variation of nutrients in farmland soils

Table 1 indicates that the available nitrogen, rapid available phosphorus, rapid available potassium content of the farmland soil of Jinjiang City and Minhou County varies greatly. Take Minhou County as an example, the content of Alkali hydrolyzable nitrogen, available phosphorus, available potassium ranges from 10.10～ 735.10mg/kg,0.80～ 667.90mg/kg and 7 ～ 683.40mg/kg, the average values are 162.18mg/kg,45.53 mg/kg,90.94 mg/k. These two types of soil organic matter content varies little, and the skewness and kurtosis of organic matter of are less than other nutrients. Compared with the two counties, the nutrients variation of the Minjiang City ranges more than Minhou County. Because the traditional statistical analysis can only generalize the soil nutrient variation, but cannot reflect its partial characteristics, namely, only reflects the overall samples, but can not quantitatively describe the stochastic , structure, independence and correlativity of soil nutrients. Therefore, to analyze and discuss the Soil Nutrient Spatial Variability structure by further adopting the geostatistics method. Table 2 has the result.

Table 2 indicates that the theoretical model of the other nutrients is in good agreement with the spherical model, except that the rapidly available potassium of Minhou County is in line with the exponential model, whose coefficient of determination is comparatively higher. The Nugget value is caused by the experimental error and the less-than-the-actual-sampling-scale, which indicates that the spatial heterogeneity of the random portion. If the Nugget is big, then a certain process on a smaller scale can not be ignored. The Nugget of soil available nitrogen, rapid available phosphorus, potassium of the two counties is relatively large, which may be related to the field management practices such as nitrogen application, methods or types etc. Generally speaking, the abutment value means the total variation within the system, the ratio of the Nugget and the Sill means that the caused by the random part accounted for the proportion of the total variation of the system, if the ratio is high, which means the spatial heterogeneity caused by the random part plays a major role. From the point of structural factors, the ratio of the Nugget and the Sill can indicate the degree of spatial correlation of the system variables. If the ratio is less than 25%, which indicates that the system has a strong spatial correlation; If it’s between 25% and 75%, then the system has a moderate spatial correlation; if more than 75% ,then it’s weak. In Minhou County, the ratios of the Nugget and the Sill of the organic matter, potassium, available phosphorus are 49.9%, 46% and 45.9%, indicating that the spatial distribution of these three nutrients is the medium spatial correlation, which may be related to soil nutrients distribution of structural and stochastic factors.Mainly influenced by the structural factors such as climate, parent material, topography, soil types etc, the three nutrients of Jinjiang City shows strong spatial correlation. While the random factors such as fertilization, tillage, planting system and other human activities make the spatial correlation of the soil nutrient decreases towards the direction of homogenization. The farmland of the organic matter of the two counties shows an interaction between structural and random factors.

Table 1 Chemical characteristics of different type of farmland with county scale

Counties	Nutrients	Samples N	Mean	Minimum	Maximum	Std. Deviation	Kurtosis	Skewness
Minhou	organic matter %	224	2.50	1.10	5.00	0.69	0.54	0.69
	available nitrogen mg/kg	2571	162.18	10.10	735.10	57.85	13.54	2.48
	available phosphorus mg/kg	2571	45.53	0.80	667.90	58.26	13.04	2.88
	available potassi um mg/kg	2571	90.94	7.00	683.40	77.71	6.35	2.19
Jingjiang	organic matter %	2385	2.23	0.41	6.19	0.86	0.51	0.52
	available nitrogen mg/kg	2385	101.05	3.00	701.00	64.00	12.20	2.45
	available phosphorus mg/kg	2385	33.99	0.90	992.50	46.41	94.82	6.97
	available potassi um mg/kg	2385	83.62	4.00	741.12	98.64	20.16	3.44

Table2 Theoretical semivariogram models of soil nutrients and corresponding parameters

Counties	Nutrients	Modals	Nugget variance c0	Partial Sill c0 + c	Nugget variance/ Partial Sill [c0/(c+c0)]	Maximum correlation distance (km)	R^2
Jingjiang	organic matter	Globular	56.5	124.2	0.455	61.0	0.739**
	available nitrogen	Globular	2200	8479	0.259	54.6	0.948**
	available phosphorus	Globular	1190	4966	0.240	61.1	0.869**
	available potassium	Globular	2510	13700	0.183	22.2	0.91**
Minhou	organic matter	Globular	0.387	0.775	0.499	210.0	0.501**
	available nitrogen	Globular	2430	7200	0.337	210.9	0.836**
	available phosphorus	Globular	2690	5858	0.459	191.9	0.644**
	available potassium	Index	5260	11438	0.460	632.7	0.574**

2.3 Soil grade index of nitrogen phosphorus potassium fertility

According to the characteristics of soil and crop of Fujian Province, combined with the Abundance and deficiency indices of the soil fertility of Fujian, we protocol the soil fertility level index of nitrogen, phosphorus, potassium, organic matter of two places(Table3). According to the standard, Jinjiang and Minhou soil nitrogen fertility being low and extremely low are 57.29% and 5.21%; Medium fertility are 26.54% and 42.82%; High and extremely high 16.27% and 51.96%. Soil phosphorus fertility of low and extremely low respectively accounts for 35.51% and 34.57%, 10.23% and 11.36% are the secondary level; High and extremely high 54.36% and 54.06%. Soil potassium fertility being low and extremely low are 69.22% and 60.56 %; Medium fertility are 5.24% and 9.76%; High and extremely high are 25.53% and 29.68%. And soil organic matter being low and extremely low are 5.452% and 0.0 %; Medium fertility are 37.11% and 22.77%; High and extremely high 57.44 % and 77.23 %. Results showed that N element is lacking in partial area, while most area is seriously lacking K element, P element is surplus in most region.

At present, soil nutrient management should focus on ensuring the nitrogenous fertilizer. While at the same time, purposefully put more potash fertilizer and less phosphate fertilizer.

Table3 Fertility grade index of soil and their distribution

Counties	Fertility index	Items	Extremely high	High	Medium	Low	Extremely low
Jingjiang	available nitrogen mg/kg	Index	>200	200-150	150-100	50-100	<50
		Sample number	130	258	633	888	476
		Percentage%	5.45%	10.82%	26.54%	37.23%	19.96%
	available phosphorus mg/kg	Index	>25	25-20	20-15	15-12	<12
		Sample number	1057	237	244	178	669
		Percentage%	44.32%	9.94%	10.23%	7.46%	28.05%
	available potassium mg/kg	Index	>120	120-100	100-80	80-60	<60
		Sample number	526	83	125	188	1463
		Percentage%	22.05%	3.48%	5.24%	7.88%	61.34%
	organic matter mg/kg	Index	>30	30-20	20-10	10-5	<5
		Sample number	427	943	885	111	19
		Percentage%	17.90%	39.54%	37.11%	4.65%	0.80%
Minhou	available nitrogen mg/kg	Index	>200	200-150	150-100	50-100	<50
		Sample number	412	924	1101	117	17
		Percentage%	16.02%	35.94%	42.82%	4.55%	0.66%
	available phosphorus mg/kg	Index	>25	25-20	20-15	15-12	<12
		Sample number	1186	204	292	205	684
		Percentage%	46.13%	7.93%	11.36%	7.97%	26.60%
	available potassium mg/kg	Index	>120	120-100	100-80	80-60	<60
		Sample number	605	158	251	333	1224
		Percentage%	23.53%	6.15%	9.76%	12.95%	47.61%
	organic matter mg/kg	Index	>30	30-20	20-10	10-5	<5
		Sample number	47	126	51	0	0
		Percentage%	20.98%	56.25%	22.77%	0.00%	0.00%

2.3The spatial distribution of soil nutrients

Differences in soil fertility exist objectively in different sampling points, the fertility grade made by the study can provide a scientific basis for the recommended fertilization and fertilizer. But due to the lack of the spatial distribution description of fertility, its pragmatic value in the guiding of the specific production can be restricted. Therefore it's very important for the soil fertility research and agricultural production to know how to reflect nutrient differences in the spatial distribution. With the help of the spatial analysis technology of GIS and the semi variance model previously got, using ordinary Kriging method for optimal interpolation in the ArcGIS9.0 platform respectively won the spatial distribution isoline map of the main nutrient content of

Jinjiang City and Minhou County, as well as the 5 levels' spatial distribution graph of soil nitrogen, phosphorus, potassium and organic matter etc (Table2). The soil nitrogen phosphorus potassium organic matter index of 5 levels of spatial distribution in two places, as shown in Figure 2, can be seen that in the county of Minhou, organic matter, nitrogen mainly was banded or mass distributed in the high value zone. The distribution of available phosphorus, potassium is very complex, The high level grade of rapid available phosphorus is in plaque distributed, mainly in the southern and central regions. The larger, lower level is a small plaque distribution in the central and northern region in China whose acreage is small and more randomly distributed. The available potassium is irregularly distributed, which shows strong spatial heterogeneity. Jinjiang City and Minhou County are very similar in nutrient spatial distribution. The distribution of available phosphorus and potassium is very complex, but the available potassium is high in the middle and has the low trend in east-west direction. The spatial distribution of nutrients can be a basic graph for the guiding of fertilization, when specifically applied, the application volume of fertilization can be adjusted according to the spatial difference of Nitrogen Phosphorus Potassium Fertility, which has strong pertinence.

3. DISCUSSION

The development of soil nutrient level is a gradual process, which will cost a period of time to study it. For example, 10 years will be necessary to better judge determine its effect on soil fertility. This paper is based on phosphorus as an example. We can see from the above research that the content of Minhou phosphorus nutrient is more than15mg/kg which accounts 65.4%, but in the early eighty, the content of Minhou phosphorus nutrient is more than 15mg/kg,accounting for 12.9%[21].The available phosphorus has increased 4 times which is greater than 15mg/kg farmland area within thirty years. Thirty years ago In Jinjiang, the proportion of greater than 20mg/kg was only 36.8%, but the current is 64.5%, increasing by 0.75times. The discourse of Rukun Lu that the farmland nutrient balance of the six provinces of South China status quo evaluation and dynamic changes of Fujian arable phosphorus balance is similar with this conclusion. The rise of the content of the phosphorus in soil indicates that most of the phosphorus in the soil is accumulating. From the consumption (biological degradation processes) and fertilizer inputs (nutrient reconstruction procedure) (nutrient balance) point of view, we can indicate that the phosphorus invested is more than the phosphorus consumed. From the macroscopic view, we can observe the nutrient degradation and construction of the plantation and can also show that the soil phosphorus of this region is in a accumulation, which have some potential dangers. While the surplus part will not only continue to increase soil phosphorus content, but will go into the environment, involving a new problem.

4. CONCLUSION

4.1 Organic matter is mainly in suitable grade; Alkali hydrolyzable nitrogen is mainly in low and suitable; Available phosphorus is mainly in appropriate and high grade; Available potassium is mainly in low grade.
4.2 The type of soil in this region is various, the land unit is small, the soil nutrient variability is significant. The total content of the nitrogen, phosphorus and potassium ranges greatly, while the test value of the soil organic matter has little variability.
4.3 The spatial variability structure in different soil content varies greatly as well as in Jingjiang City and Minhou County. The available nutrient of Jingjiang is influenced by the structural element, while in Minhou, the structure and randomness both execute their influence. While in the soil organic matter, both places have them influenced by the co-action of structural and random elements.

ACKNOWLEDGEMENTS

This paper is funded by the National Natural Science Foundation of China (41001049); the Fujian Natural Science Foundation (2009J05053), Ministry of Science and Technology of China (2010DFB10030); the Key Program of National Natural Science Foundation of China (40930101); the National Basic Research Priorities Program of China (2007FY120100; the Commonweal Foundation of China's National Academy (201220229).

REFRENCES

[1]Franzen ,D. W., Hofman,V. L., Halvorson, A. D., Cihacek., L. J. ,1996. Sampling for sitespecific farming: Topography and nutrient considerations[J]. Better Crop, 80(3):14-18.

[2]Wild, A. ,1971.The potassium status of soils in the savanna zone of Nigeria[J]. Expl. Agric., 7: 257-270.

[3]Tening,A. S., Omueti,J. I., 1995.Potassium status of some selected soils under different landuse systems in the sub humid zone of Nigeria. Commun[J]. Soil Sci. Plant Anal., 26(5&6):657-672.

[4]Ovalles,F. A., Collins,M. E.,1986.Soil landscape relationships and soil variability in north central Florida[J]. Soil Sci. Soc. Am. J., 50: 401-408.

[5]Miller,P. M., Singer,M. J., Nielsen,D. R. , 1988.Spatial variability of wheat yield and soil properties on complex hills[J]. Soil Sci. Soc. Am.J., 52: 1133-1141.

[6]Bhatti,A. U., Mulla,D. J., Frasier,B. E., 1991.Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and the matic mapper images[J]. Remote Sens. Environ., 37:181-191.

[7]Mulla,D. J. , 1993.Mapping and managing spatial patterns in soil fertility and crop yield[A]. In: Robert PC, Rust RH, Larson WE, eds. Soil specific crop management [C]. ASA, CSSA, SSSA,Madison, WI, 15-26.

[8]Franzen,D. W., Cihacek,L. J., Hofman,V. L.,1996.Variability of soil nitrate and phosphate under different landscapes[A]. Proceedings of the 3th in international conference on precision agriculture [C]. Minneapolis, Minnesota, ASA, CSSA, SSSA, 521-529.

[9] Beckett,P. H. T, Webster,R.,1971.Soil variability: A review[J]. Soils and Fertilizers, 34: 1-15.

[10] Warrick,A. W., Nielsen,D. R. ,1980. Spatial variability of soil physical properties in the field[A]. In: Applications of soil physics[C]. Hillel D. (ed.). Academic Press, London, 319-344.

[11] Scott,H. D. et al., 1994. Temporal variability of selected properties of Loessial soil as affected by cropping[J]. Soil Sci. Soc. Am. J., 58: 1531-1538.

[12]Burgess,T.,M., Webster,R.,1980.Optimal interpolation and isarithmic mapping of soil properties. The semivariogram and punctual kriging[J] Soil Sci, 31: 315-331·

[13]Goovaerts,P.,1999.Geostatistics in soil science: state-of-the-art and perspectives. Geoderma, 89: 1-45

[14]Bergstrom, D. W., Monreal,C. M., Millette,J. A.et al., 1998. Spatial dependence of soil enzyme activities along a slope. Soil Sci-ence Society of America Journal. 62:1302-1308·

[15]Yost,R. S., Uehara,G., Fox,R. L.,1982.Geostatistical analysis of soil chemical properties of large land areas: II. Kriging. Soi lScience Society of America Journal, 46: 1033-1037

[16]Bai,Y. L.,Li,B. G.,Hu,K. L.,1999.Research of Huang-huai-hai plain soil salt and its composition of space variation characteristics[J] Soil Fertilizer, 21(3):22-26.

[17]White,J. G., Welch,R. M., Norvell,W. A.,1997.Soil Zinc map of the USA using geostatistics and geographic information systems[J]. Soil Sci. Soc. Am. J., 61: 185-194.

[18]Lu,R.K.,2000.Soil agricultural chemical analysis method[M].Beijing,China Agricultural Science and Technology Press. 146-196.

[19]Yang,K.C.,2006.GIS software applied experimental instruction.

[20]Lu,R. K.,Shi,Z. Y.,Shi,J. P. 6 provinces in southern China farmland nutrient balance status evaluation and dynamic change research[J]. China Agricultural Science Press.

[21] 1981.Minhou county soil census office. MinHou soil.

Spatial Variability of Nutrient Properties in Soil of Jilin Middle Plain

Li Zhibin[1], He Yingbin[2]

1. LUOSIDA Digital Remote Sensing Technology and Application Company Limited;

2. Institute of Agricultural Resources and Regional Planning, CAAS

lzb419@163.com

Abstract - Spatial distribution of soil middle-elements and microelements in the middle plain of Jilin province were investigated using geostatistics and geographic information system (GIS) techniques. With various processing methods, including logarithmic transformation, excluding outliers and Box-Cox transformation, the available Ca, Mg, B, Cu, and Zn contents were evaluated with normal distribution. The result shows that Box-Cox transformation is applied in order to achieve normality in the data sets of available Ca, Mg, Cu, and Zn while excluding outliers were employed in the data set of available B to dampen the effect of outliers. Geostatistical analyses were carried out, including calculation of experimental variograms and model fitting, and then the distribution patterns of these soil nutrients elements were plotted. Semivariogram analysis showed that these soil nutrient elements were moderately spatially dependent in a given range.

Keywords - Soil properties;Spatial variability; Geostatistics;GIS;Northeast China

INTRODUCTION

Spatial variability of soil properties is inherent in nature. And it always exists whether it is observed in large-scale or small-scale[1]. A better understanding of the spatial variability of soil nutrients is important for refining the agricultural management practices and for improving sustainable land use. Quantification of soil spatial variability is important in ecological modeling, environmental prediction, precision agriculture, and natural resources management[2].

Soil surveys provide a map of different soil orders, together with a record of measured observations for each sampling locations. However, for a large scale soil property map it is not practical to measure soil properties for locations[3].

Although spatial distribution of soils provided by soil surveys is sufficient to make decisions for land use, more detailed information is needed in order to set up models to simulate chemical fate and transport, as well as for precision farming programs.

Geostatistics is a technology for estimating the soil property values in non-sampled areas or areas with sparse sampling[4]. It Provides a set of statistical tools for a description of spatial patterns, quantitative modeling of spatial continuity, spatial prediction, and uncertainty assessment[5]. Geostatistical techniques incorporating spatial information into predictions can improve estimation and enhance map quality. Although standard geostatistical techniques have been suitable for describing the spatial distribution of soil and successfully analyze spatial variability of soil properties, most applications were estimated in small-scale areas or on a field scale with little work being done in large land areas or soil regions. And also considerable interests have been generated in assessment of the macro elements (N, P, and K et al.) of agricultural soils, while less study about the middle-element and micro-element.

In this study, classical statistics and Geostatistics analysis methods, in combination with geographic information systems (GIS), were used to study the spatial variation characteristics of several soil properties.

The objectives of this study were to map soil properties and provide a scientific basis for cultivated land evaluation which is targeting at improving soil quality in this region and analyzing the effect on grain production from the cultivated land quality change.

MATERIALS AND METHODS

Study area

The study area (123°06′ ~ 127°06′E, 42°49′ ~ 45°32′N) is located at the middle part of Jilin Province, Northeast China(see Fig.1.) . This area has an altitude below 200m with an area of 45973 km2, among which cultivated land account for 61.9%. This region has been the major grain production areas in Jilin Province.

The study area is characterized with a temperate, semi-humid continental monsoon climate. The mean annual temperature is about4-5℃and the average annual precipitation is 500-600mm. The average of sunshine each year is between 2200-3000h. The frost-free period is about 130-145d. The soils are largely comprised of black soil (Luvic Phaeozem, FAO), chernozem (Haplic Chernozem, FAO), meadow soil (Eutric Vertisol, FAO), aeolian soil (Arenosol, FAO) and paddy soil (Hydragric Anthrosol, FAO).

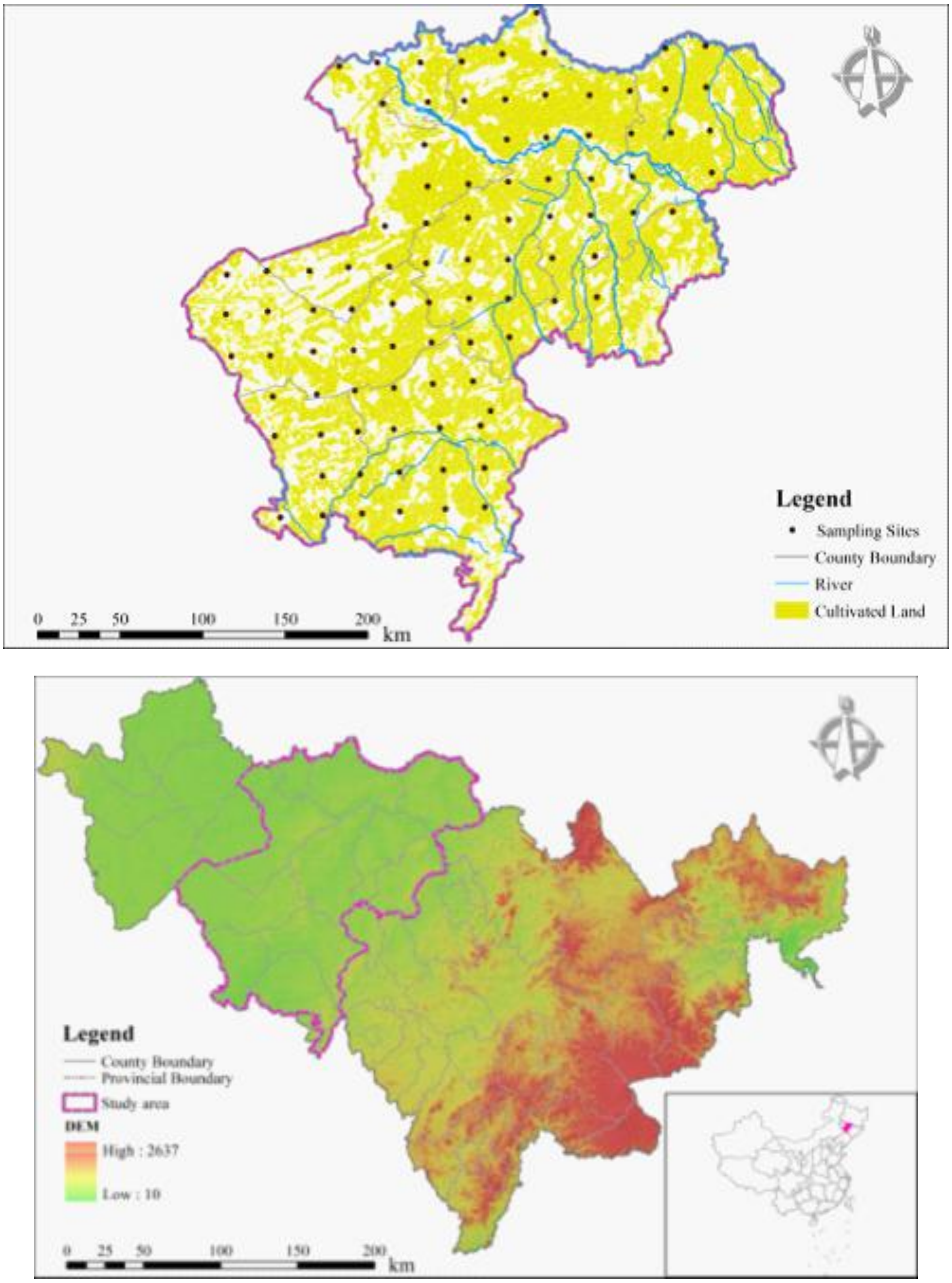


Fig. 1. Location map of study area and soil sampling sites
in Jilin Province, Northeast China (n = 68).

Soil sampling, processing, and analysis

In the May of 2005 over the entire arable crops region a total of 70 soil samples from the plow layer (0-20 cm) at an approximate interval of 30 km were collected. Global position system (GPS) was used to determine the sampling locations. Soil samples were air-dried and ground to pass through a 2-mm sieve. The amount of available soil calcium (Ca), magnesium (Mg), boron (B), cuprum (Cu) , zinc (Zn) in each sample were determined by the ASI systematic approach[6] [7], which is high efficiency, fast analysis and high accuracy by using the complete sets of equipment and systematic techniques and procedures.

Classical statistics and geostatistical analysis

Some main statistical parameters, which are generally accepted as indicators of the central tendency and spread of the data, were analyzed. These include description of the mean, standard deviation, variance, coefficients of variation (CV) and extreme maximum and minimum values. To decide whether or not the data followed the normal frequency distribution, the coefficients of skewness and kurtosis were examined[8]. These statistical parameters were calculated using EXCEL 2003 and SPSS 11.5.

Geostatistics is a spatial analytical method developed based on classical statistics. Semivariogram of Geostatistics was conducted to test the spatial autocorrelation within the data of soil properties that was not interpreted by classical statistics. Compared with classical statistics, it can be more easily combined with GIS and associate the spatial patterns with the ecological processes.

Prior to geostatistics analysis, the spatial distances of the soil sampling locations must be determined. Soil sampling locations were input into ArcGIS software, in which the latitudes and longitudes were transformed to X- and Y-coordinates with distances in meters.

Geostatistics uses the semi-variogram to quantify the spatial variation of a regionalized variable, and provides the input parameters for the spatial interpolation method of Kriging[9] [10]. The semi-variogram is half the expected squared difference between paired data values z(x) and z(x+h) to the distance h, by which locations are separated[11].

RESULTS AND DISCUSSION

Descriptive statistics

Variability of soil property can be described by average, standard deviation (SD) and coefficient of variation (Cv). Among them, Cv is the most discriminating factor. When Cv is <10%, the property shows low variability; and if Cv is more than 90%, it shows great variability[12] [13]. The characters of soil variability are shown in Table 1. All the Cvs are between 10% and 90%. This indicates that available Ca, Mg, B, Cu, Zn are moderate variability in the study area.

Table 1 Classical statistics result for soil middle-elements and microelements in Jilin Middle Plain

Variable	Sample	Mean(mg/L)	Variance	Skewness	Kurtosis	Cv
Available Ca	68	3100.22	1395.02	0.82	0.45	45.00
Available Mg	68	418.23	254.59	1.02	1.08	60.87
Available B	68	1.64	0.79	2.62	13.70	48.38
Available Cu	68	2.18	1.13	1.34	1.63	51.99
Available Zn	68	1.34	0.92	2.34	6.76	68.28

We also analyzed the quantitative parameters of the probability distribution and the significance level of the Kolmogovorv-Smirnov test for conformance to a normal distribution for the variables the available Ca, Mg, B, Cu, and Zn contents with various processing methods, including logarithmic transformation, excluding outliers and Box-Cox transformation.

The K-S showed that available Ca, Mg, Cu, and Zn didn’t exhibit a normal distribution in this study area. They couldn’t pass one-sample Kolmogovorv-Smirnov (K–S) test at a significant level ($p < 0.05$) and could not be directly used in the analysis of variation function. Therefore, the Box-Cox transformation is applied in order to achieve normality in the data sets of available Ca, Mg, Cu, and Zn while excluding outliers were employed in the data set of available B to dampen the effect of outliers.

GEOSTATISTICS ANALYSIS

The semivariogram for Availabe Ca, Mg, B, Cu, and Zn are shown in Fig. 2. Key parameters of the remaining semivariogram are given in Table 3. Their optimal theoretical models were gaussian, circular, exponential, exponential, and gaussian model, respectively.

The range of the semi-variograms was the distance at which semi-variance attained the maximum value (sill), and the sill approximately equaled the same variance[14] (Journel and Huijbergts, 1978). The range expressed as distance could be interpreted as the diameter of the zone of influence that represented the average maximum distance over which a soil property of two samples was related. At distance less than the range, measured properties of two samples became similar with decreasing distance between the two points. Thus, the range provided an estimate of areas of similarity. The zones of influence for available Ca, Mg, B, Cu and Zn were approximately from 118.46km to 247.07km. These distances stood for the minimum distances on the average, at which maximum variation occurred, and were larger than the distances among sampling locations.

Spatial distribution of the five soil nutrients

Kriging was used to convert point soil samples into continuous fields of soil properties. The parameters of geostatistics obtained above were used for Kriging to produce an interpolation map of the five soil nutrients in soils of the study areas. A search region of 12 nearest-neighbours was applied. For the spatial interpolation, a cell size of 1km1km was chosen to divide the study area into a grid system. The final result of this spatial interpolation process was shown in Figure 4. The available Ca content had a large spatial variability, namely, it increased from west to east with the distribution of vertical stripe. The soil with high available Ca content is found in the middle part of the study area, which mainly lied in Jiutai county, Dehui county and Nong'an county. And the major soil type is black soil and meadow soil in high available Ca content areas.

The available Mg content in soil showed a downward trend from east to west, while the high-value areas are mainly concentrated in the rive infested areas, and along the direction of the river the available Mg content is gradually reduced. Such regions are distributed in meadow soil and black soil of Yushu county, Dehui county, Jiutai county and the southeastern of Gongzhuling and Lishu county.

However, for available B and Cu, there was no obvious visual trend. There are a number of high-value areas scattered patches in this area, and patch size and shape is of significant differences in spatial distribution. The nutrient content is still follow the distribution of the gradient from high to low, in which area with high available B content is mainly distributed in the west of the study area, the soil type in these regions are mostly chernozem and meadow soil; and the distribution of available Cu content in general was related to altitude, the regions with higher elevations in eastern part had the higher available Cu content than that in the western regions with low elevation. And there have been a number of high-value areas locally affected by random factors, these high-value areas are mainly distributed in the northeastern and southeastern part of the study area.

Table 2 Classical statistics result for available Ca, Mg, B, Cu, Zn (soil middle-elements and microelements concentrations) and their K-S test after different data processing methods

Variable	Treatment method	Mean (mg/L)	S.D	Minimum (mg/L)	Maximum (mg/L)	Skewness	Kurtosis	K-S P
Available Ca	Original data	3100.22	1395.02	837.65	6741.45	0.82	0.45	0.56
	Excluding outliers	3100.22	1395.02	837.65	6741.45	0.82	0.45	0.56
	Logarithmic transformation	7.94	0.47	6.73	8.82	-0.31	-0.18	0.73
	Box—Cox	25.72	3.46	17.76	32.86	-0.02	-0.30	0.85
Available Mg	Original data	418.23	254.59	96.00	1297.60	1.02	1.08	0.11
	Excluding outliers	415.16	244.90	96.00	1088.65	0.79	0.04	0.10
	Logarithmic transformation	5.85	0.63	4.56	7.17	-0.12	-0.91	0.53
	Box—Cox	7.92	1.12	5.75	10.37	-0.02	-0.91	0.59
Available B	Original data	1.64	0.79	0.25	6.05	2.62	13.70	0.13
	Excluding outliers	1.60	0.62	0.25	3.45	0.50	1.19	0.80
	Logarithmic transformation	0.39	0.49	-1.39	1.80	-1.12	4.13	0.09
	Box—Cox	0.46	0.54	-1.09	2.55	0.17	3.59	0.34
Available Cu	Original data	2.18	1.13	0.65	5.90	1.34	1.63	0.13
	Excluding outliers	2.17	1.10	0.65	5.25	1.22	1.06	0.16
	Logarithmic transformation	0.66	0.48	-0.43	1.77	0.24	-0.29	0.86
	Box—Cox	0.60	0.42	-0.45	1.50	0.01	-0.26	0.92
Available Zn	Original data	1.34	0.92	0.30	5.40	2.34	6.76	0.03
	Excluding outliers	1.31	0.81	0.30	3.95	1.77	3.32	0.05
	Logarithmic transformation	0.13	0.56	-1.20	1.69	0.38	0.58	0.81
	Box—Cox	0.09	0.54	-1.36	1.43	-0.01	0.57	0.89

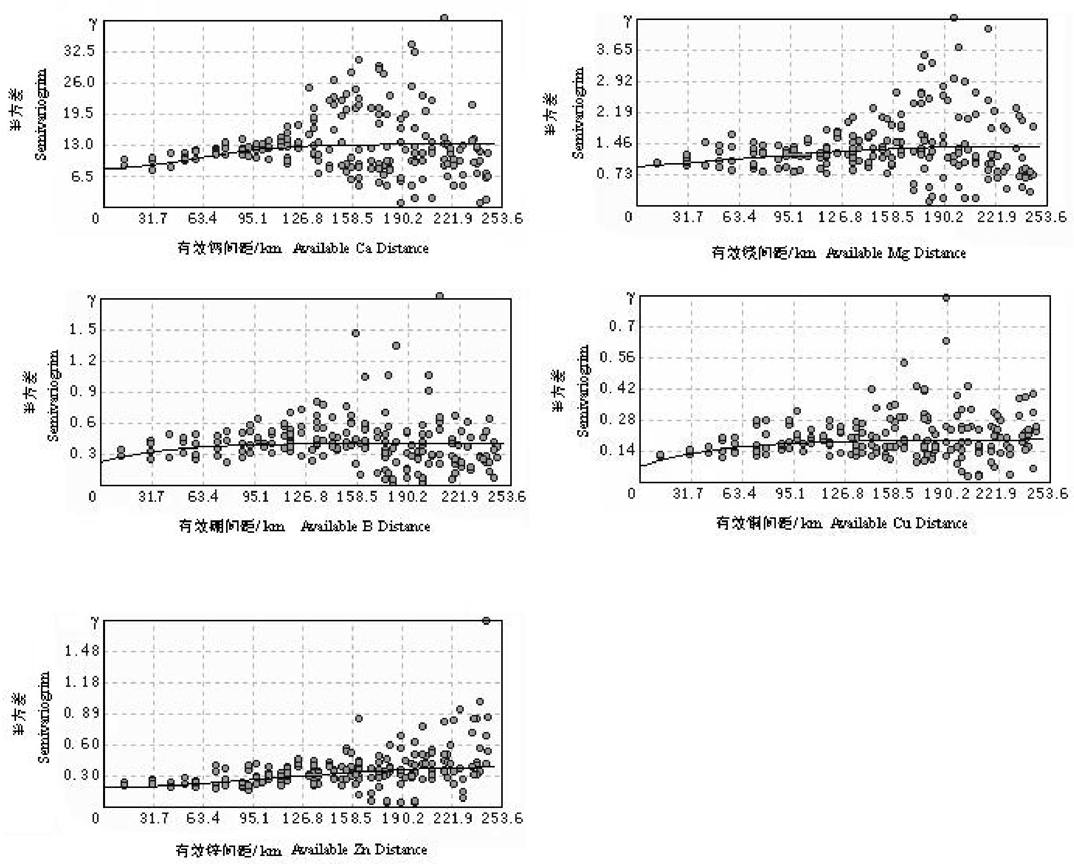


Fig.2 Experimental semivariograms with fitted models for Available Ca, Mg, Cu, B, and Zn of Jilin Middle Plain in Northeast China

Table 4 Parameters of the variogram model for soil middle-elements and microelements

Variable	Model	Nugget	Sill	Nugget/Sill(%)	Range(km)
Available Ca	Gaussian	8.15910	13.20850	61.77	139.95
Available Mg	Circular	0.91492	1.37586	66.50	191.84
Available B	Exponential	0.22133	0.40829	54.21	118.46
Available Cu	Exponential	0.07068	0.19343	36.54	146.88
Available Zn	Gaussian	0.18815	0.39051	48.18	247.07

The spatial changes of soil available Zn content had more regularity. It showed ladder-like decline from southeast to northwest. The west part of the study area had the lowest available Zn content. While the regions with high available Zn content located in the northeastern, where the soil type is chernozem, calcareous meadow soil, wind sand. It is contrary to the truth that soil type in these regions should have the lower available Zn content[15], so we could determine that the random factors make these regions with higher available Zn content. Long-term application of nitrogen fertilizer, phosphorus and potassium fertilizer can increase the soil available Zn content[16]. It was found that the eastern part of the study area is the major corn-producing areas, the application of large quantities of nitrogen fertilizer and phosphorus fertilizer containing Zn resulted in the imbalance of the input and output of Zn in the ecosystem, the input section is greater than the output part.

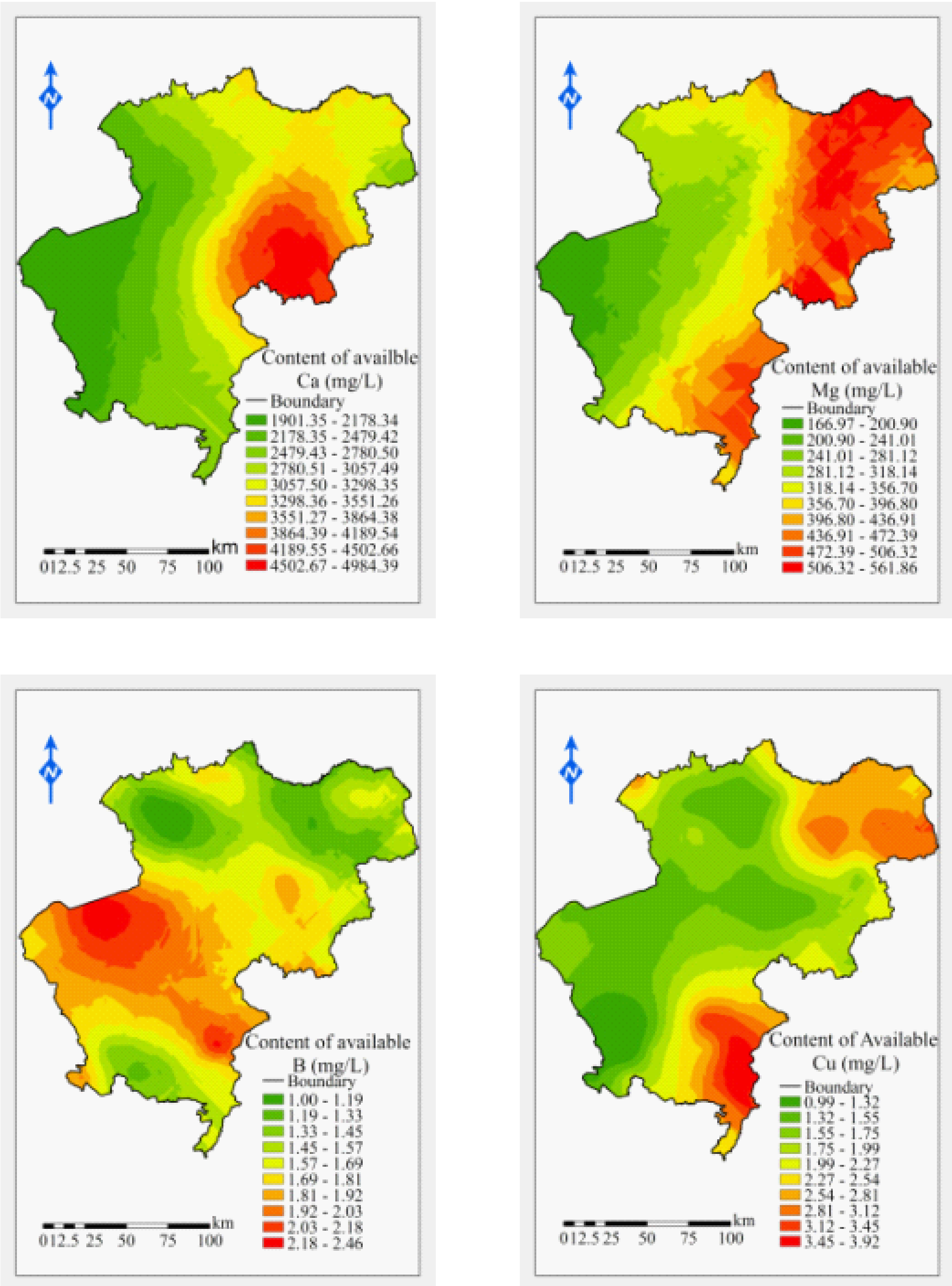
CONCLUSIONS

All the soil properties, namely, available Ca, Mg, Cu, B, and Zn, had spatial autocorrelations. The classic statistical analysis showed that all soil properties had moderate variability with 0.1CV0.9. While the geostatistical analysis results showed all soil nutrients had moderate spatial correlations with the nugget/sill ratio of

0.25-0.75 that random and structural factors codetermined. In addition, kriging could successfully interpolate all soil nutrient content. In general, then, the geostatistics method on a large scale could be accurately used to evaluate spatial variability of soil medium elements and micro elements in Jilin Middle Plain of Northeast China.

ACKNOWLEDGEMENTS

This paper is funded by the National Natural Science Foundation of China (41001049); the Ministry of Science and Technology of China (2010DFB10030); the Key Program of National Natural Science Foundation of China (40930101); the National Basic Research Priorities Program of China (2007FY120100) ; the Commonweal Foundation of China's National Academy (201220229).



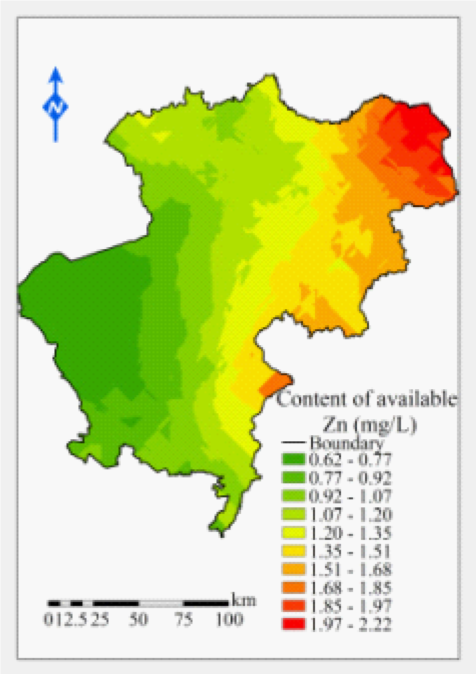


Fig.4 Spatial distribution map of available Ca, Mg, B, Cu and Zn in Jilin Middle Plain, Northeast China

REFERENCES

[1]Cheng,X. F., Shi,X. Z., Yu,D. S. et al., 2004. Spatial variance and distribution of total nitrogen and organic matter of soil in Xingguo county of Jiangxi, China. Chin J Appl Environ Biol 10(1): 064-067.

[2]Wei, J. B., D.-N. Xiao, et al. ,2008. Spatial variability of soil properties in relation to land use and topography in a typical small watershed of the black soil region, northeastern China. Environmental Geology 53(8): 1663-1672.

[3]Zhang, X. ,Y. Y. Y. ,Sui, et al. ,2007. "Spatial variability of nutrient properties in black soil of northeast China." Pedosphere 17(1): 19-29.

[4]Yao, L. X., Zhou, X. C., Cai, Y. F. , Chen, W. Z. 2004. Spatial variability of soil properties at different sampling intensites and accuracy of their estimation. Soils (in Chinese). 36(5): 538-542.

[5]Goovaerts, P.1999. Geostatistics in soil science: State-of-the-art and perspectives. Geoderma. 89: 1-45.

[6]Hunter, A. H. 1980. Laboratory and greenhouse techniques for nutrient survey to determine the soil amendments required for Optimum plant growth. Mimeograph. Agro Service International, Florida, USA.

[7]Portch, S. and A. Hunter. 2002. A systematic approach to soil fertility evaluation and improvement Modern Agriculture and Fertilizers, PPI/PPIC China Program Special Publication NO.5.

[8]Paz-Gonzalez, A., Vieira, S. R., Castro,T. ,2000.The effect of cultivation on the spatial variability of selected properties of an umbric horizon. Geoderma, 97: 273–292.

[9]Matheron, G., 1963. Principles of geostatistics. Econ. Geol. 58, 1246–1266.

[10]Krige, D. G., 1951. A statistical approach to some basic mine valuation problems on the Witwatersrand. J. Chem. Metall. Mining Soc. South Africa 52 (6), 119–139.

[11]Webster, R., Oliver, M., 2001. Geostatistics for Environmental Scientists. John Wiley & Sons, Chichester, UK.

[12]Wang,Z. Q. ,2001.Geostatistics and its application in ecology. Science Press, Beijing, pp 162–192.

[13]Zhang,J. B., Song,C. C., Yang,W. Y.,2007.Tillage effects on soil carbon fractions in the Sanjiang Plain, northeast China. Soil Tillage Res 93:102–108.

[14]Journel, A. G. and Huijbregts, Chen,J. 1978. Mining geostatistics. Academic Press, New York. 595pp.

[15]Liu,Z.,1996.Soil trace elements in China [M] (in Chinese). Nanjing, Phoenix Science Press,

[16]Li,H. T., Zhao,B. S., Li,C. W., et al.,1995.Trace elements in agro-ecological system of Lou soil II The effect of organic manure on the balances of Zn Mn and Cu in the crop-soil (in Chinese). Journal of Northwest Sci-tech University of Agriculture and Forestry. 23(4):25-30.

Yield Prediction for Winter Wheat in North China by Using IPCC-AR4 Model Data

Zhang Mingwei [1], Fan Jinlong [1], Deng Hui [2],, Ren Jianqiang [2,3], Li Guicai [1], Chen Zhongxin [2,3]

1. National satellite Meteorological Center, Beijing, China, 10081;

2. Key Lab. of Resources Remote Sensing & Digital Agriculture, Ministry of Agriculture, Beijing, China 10081;

3. Institute of Agriculture Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing, China 10081

fanjl@cma.gov.cn

***Abstract*—Spatial and temporal mismatches between coarse resolution output of global climate models (GCMs) and fine resolution data requirements of crop models are the major obstacles for assessing the site-specific climatic impacts of climate change on the production of winter wheat. Based on the output of IPCC AR4 model and observation data, statistical downscaling of precipitation, minimum temperature, and maximum temperature in North China was analyzed. With the combination crop model and climate mode, the effects of climate change on the winter wheat production of North China were simulated. Some conclusions from the study might be drawn as follows: Under the IPCC-B1 Scenario, the length of winter wheat growing season in North China would be shortened from 2010 to 2099, and its yield would be decreased.**

Keywords- climate change;crop model; winter wheat; North China

1. INTRODUCTION

Climate is the major driving force of crop production and water use (Harmsen et al., 2009; Fang et al., 2010). Climate change is very likely to affect future crop growth. Increasing temperatures in winter and spring will lead to season shift with earlier and faster crop phenological development. Higher temperatures in summer will most likely affect photosynthesis negatively and obstruct biomass production. Absence of rainfall will necessitate irrigation in today rain-fed crop systems. Under climate changes, the potential for such projected changes to increase the risks of floods, but the potential damages in particular regions need to be assessed (SWCS, 2003).

Simulation models are frequently used to investigate the potential impacts of climate on crop growth and how crop yield responds to climate change (Keating et al., 2003; Tan and Shibasaki, 2003; Wang et al. 2008; Lu et al., 2008). By using Water Erosion Prediction Project (WEPP) model and global climate models (GCMs) output, Zhang (2005) predicted that the increase of productivities and evapotranspiration of wheat and maize over the Loess Plateau during 2070-2099 would be due to increase of precipitation. Challinor et al. (2010) predicted that climate change would result in increased crop failure in Northeast China using models and socio-economic data.

WOFOST (WOrld FOod STudies) is a simulation model for the quantitative analysis of the growth and production of annual field crops. It is a mechanistic model that explains crop growth on the basis of the underlying processes, such as photosynthesis, respiration and how these processes are influenced by environmental conditions. With WOFOST, we can calculate attainable crop production, biomass, water use, etc. for a location given knowledge about soil type, crop type, weather data and crop management factors (e.g. sowing date). WOFOST has been used by many researchers over the World and has been applied for many crops over a large range of climatic and management conditions. Moreover, WOFOST is implemented in the Crop Growth Monitoring System which is used operationally to monitor arable crops in Europe and to make crop yield forecasts for the current growing season (Nassiri et al., 2006; Catalin et al., 2009; Vossen, 1995).

Spatial and temporal mismatches between coarse resolution output of global climate models (GCMs) and fine resolution data requirements of crop models are the major obstacles for assessing the site-specific climatic impacts of climate change on the production of winter wheat (Cubasch et al., 1996). Both dynamic and statistical approaches are used to downscale GCM projection to finer spatiotemporal scales. Dynamic downscaling is computationally costly (Risbey and Stone, 1996; Solman and Nunez, 1999) and is only available for limited regions.

This study aims to predict the change of winter wheat yield in North China by using IPCC-AR4 model data using WOFOST model. Based on the output of IPCC AR4 model and observation data, statistical downscaling of precipitation, minimum temperature, and maximum temperature in North China was analyzed. With the combination crop model and climate model, the effects of climate change on the winter wheat production of North China were simulated.

2. STUDY AREA AND DATA

2.1. Study area

The study area is located in the Huanghuai region in China, including Beijing and Tianjin municipalities, and the Hebei, Shandong, Henan and Shandong provinces, in which is the main cereal production base in China (Figure 1). The area of this region is approximately 539,508 km2. Crop land dominates the relatively flat landscape of the Northern China Plain, comprising about 62.91% of the total area. The crops in this area are main dry-land types, such as winter-wheat, maize, cotton and their planting acreage accounts for about 1/3 of that in whole China. The planting acreage of winter wheat is 56% of that in China in 2003 (China Agriculture Statistical Report, 2004).

2.1. Climate data

The climate change scenario of IPCC-B1, projected under IPCC SRES B1 using the CMIP3 multi-model, was used in this study. The spatial resolution of CMIP3 data is 1°by 1° (latitude by longitude).

The 0.5°by 0.5° (latitude by longitude) daily mean, maximum, and minimum temperature dataset and 1°by 1° (latitude by longitude) daily precipitation dataset for the period of 1971-2000 over mainland China were acquired from the National Climate Center of China.

3. METHODS

3.1. Spatiotemporal downscaling

The CMIP3 monthly temperature and precipitation from 1971 to 2000 was used as the control, and the historical monthly temperature, and precipitation from 1971 to 2000 as the baseline. For each calendar month, the ranked observational monthly temperature/precipitation was plotted with the ranked the ranked CMIP3 model output. Simple univariate linear and non-linear functions were fitted to each plot to obtain transfer functions for each month. Those transfer functions were used to downscale the 2010-2099 monthly temperature/precipitation of the CMIP3 output to monthly temperature/precipitation in North China.

In this study, CLIGEN was used to disaggregate CMIP3 model monthly output to daily weather series (Zhang, 2004). Measured daily weather data of climate data of 1971-2000 in North China were used to estimate the baseline CLIGEN input parameters. Adjusted precipitation parameter and downscaled CMIP3 monthly temperature/precipitation were input to CLIGEN, and daily weather data of CMIP3 climate scenario from 2010 to 2099 were generated for North china.

3.2. Simulated crop growth under future climate

Three input files (i.e., crop parameter, climate and soil) are needed to run WOFOST model. The soil properties derived from soil map of China were used to build soil input files. Measured crop parameters of winter wheat in North China were build crop input files. The crop, soil and daily weather data were input to WOFOST, and yearly winter wheat yield of CMIP3 climate scenario from 2010 to 2099 were generated for North China.

4. RESULT AND DISCUSSION

4.1. Validation

The comparison between the simulated winter wheat yield and the situ data (Figure 1) indicated the number of cases that the data lie on the 1:1 line (slope = 0.909, R2 = 0.736). This indicates the WOFOST model is feasible for simulating winter growth in North China.

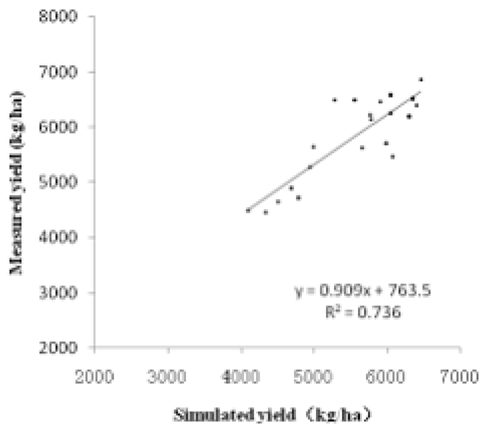


Figure 1. Divergence point diagram between simulated and statistic yields for Daxing of Beijing, Gucheng of Shandong province, and Dezhou of Shandong province (1993~2000, data is missing in 1996)

4.2. The impacts of climate change on winter wheat growth

The length of winter wheat growth season would decreases in North China under IPCC-B1scenario (Figure 2). The length of growing season decrease was due to a moderate increase of temperature in spring.

In mostly years, the yield of winter wheat would decrease under future climate (Figure 3). The trend of yield change was not agreed with decrease growing season length. The decrease of growing season length was result in yield decrease. Higher temperatures were affect photosynthesis negatively and obstruct biomass production.

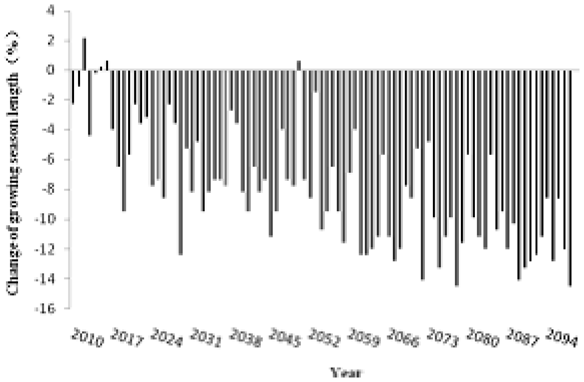


Figure 2. Change of winter wheat growing season length in North China under the IPCC-B1 scenario (2010~2099)

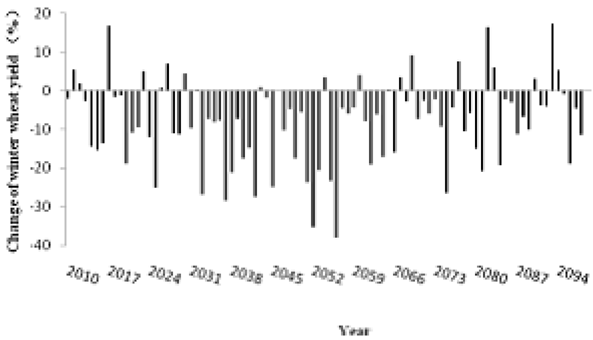


Figure 3. Change of winter wheat yield in North China under the IPCC-B1 scenario (2010~2099)

5. CONLUSIONS

Based on the CMIP3 model output and observation data, statistical downscaling of temperature and precipitation in North China was analyzed. Using crop model, the effects of climate change on the winter wheat production of North China were simulated. Some conclusions from the study might be drawn as follows: Under the IPCC-B1 Scenario, the length of winter wheat growing season in North China would be shortened from 2010 to 2099, and its yield would be decreased.

6. ACKNOWLEDGEMENTS

This study is funded by National High Technology Development Program of China contract number 2008AA10Z217. We acknowledge the modelling groups for providing their data for analysis , the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project for collecting and archiving the model output, organizing the model data analysis activity. The data has been collected, analyzed, and are provided by National Climate Center of China.

7. REFERENCES

[1]Catalin, L., Bettina, B., Fabio, M. Anca, L. D. , 2009. “Adaptation of WOFOST model from CGMS to Romanian condition,” Journal of Plant Development, 16, pp. 97-102.

[2]Challinor, A. J., Simelton, E. S., Fraser, E. D. G., Hemming, D., Collins, M., 2010. “Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China,” Environmental Research Letters, 5, pp. 034012, DOI: 10.1088/1748-9326/5/3/034012.

[3]Cubasch, U., von Storch, H., Waszkewitz, J., Zorita, E., 1996.“Estimate of climate changes in southern Europe using different downscaling techniques,” Climate Research, 7, pp. 129-149.

[4]Fang, Q.X., Ma, L.W., Yu, Q., Ahuja, L.R., Malone, R.W., Hoogenboom, G., 2010.“Irrigation strategies to improve the water use efficiency of wheat-maize double cropping systems in North China Plain,” Agricultural Water Management, 97, pp. 1165-1174.

[5] Harmsen, E. W., Miller, N. L., Schlegel, N. L., Gonzalez, J. E.,2009.“Seasonal climate change impacts on evapotranspiration, precipitation deficit and crop yield in

Puerto Rico," Agricultural Water Management, 96, pp.1085-1095.

[6]Keating, B. A., Carberry, P.S., Hammer, G. L., Probert, M.E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., Smith, C. J., 2003."An overview of APSIM, a model designed for farming systems simulation," European Journal of Agronomy, 18, pp. 267-288.

[7]Liu, S. X., Mo, X. G., Lin, Z. H., Xu, Y. Q., Ji, J.J ., Wen, G., Richey, J., 2010."Crop yield responses to climate change in the Huang-Huai-Hai Plain of China," Agricultural Water Management. 97, pp. 1195-1209.

[8]Nassiri, M., Koocheki, A., Kamali, G. A., Shahandeh, H., 2006."Potential impact of climate change on rainfed wheat production in Iran," Archives of Agronomy and Soil Science, 52, pp. 113-124.

[9]Risbey, J., Stone, P., 1996. "A case study of the adequacy of GCM simulations for input to regional climate change," Journal of Climate, 9, pp. 1441-1467.

[10]Solman, S., Nunez, M., 1999 ."Local estimates of global climate change: a statistical downscaling approach," International Journal of Climatology, 19, 835–861.

[11]SWCS,2003.Conservation implications of climate change: Soil erosion and runoff from cropland, A Report from the Soil and Water Conservation Society. Soil and Water Conservation Society, Ankeny, Iowa. http://www.swcs.org/docs/climate change-final.pdf.

[12]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.

[13]Vossen, P., 1995.Early crop yield assessment of the E. U countries: the system implemented by the Joint Research Center, EUR Publication of the office for Official Publications of the E. C. Luxembourg.

[14]Wang, E. L., Yu, Q., Wu, D. R., Xia, J., 2008. "Climate, agricultural production and hydrological balance in the North China Plain," International Journal of Climatology, 28, pp. 1959-1970.

[15]Zhang, X.-C.,2005."Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion," Agricultural and Forest Meteorology, 135, pp. 215-229.

[16]Zhang, X.C.,2004."Calibration, refinement, and application of the WEPP model for simulating climatic impact on wheat production," Trans. ASAE, 47, pp. 1075–1085.

An Overview of the Use of Remote Sensing and GIS for Paddy Crop Monitoring and Yield Estimation to Strengthen National Food Security in Indonesia

Rizatus Shofiyati[1], Muhrizal Sarwani[2], and Wahyunto[1]

1. Indonesian Agency for Agric.Research & Development (IAARD) 2. Indonesian Center for Agricultural Land Resources Research and Development (ICALRD)

rshofiyati@yahoo.com

***Abstract*-Indonesia has a large paddy field area, around 7.86 million hectares. Rice is one of five commodities that is target of self-sufficiency of Indonesia in period 2010 to 2014, and the surplus target of 10 million tons in 2014. Agricultural land has a strategic function as main food provider for people of Indonesia. It is required both short and long term planning to meet rice self-sufficiency. A variety of agricultural information, especially the cultivated area, growth and yield of major crops, is an important basis to make food policy and economic planning for a economy. At present, crop acreage, production and other agricultural information released by National Bureau of Statistics of Indonesia are mainly obtained in two ways: the traditional overall report (summary of several administrative levels) and the directory sampling based on classical statistics. They need to be supported by alternative innovative technologies. One is using remote sensing data and technology. This paper presents an overview of the use of remote sensing and GIS technology used for operational agricultural crop monitoring in Indonesia.**

Keywords—remote sensing; crop monitoring; rice yield estimation

I. INTRODUCTION

Indonesia has a large paddy field area, around 7.86 million hectares (Haryono in Harian Kompas, 15 March 2012). Almost 40% Indonesian paddy field are situated in Java Island. The 60% of national food production has been supplied by Java Island. The need of rice in Indonesia is around 58.6 million tons (Dry Milled Rice) in 2025. It is required approximately 12.91 million hectares of Paddy field (Irianto, 2011). It means that agricultural land has a strategic function as main food provider for people of Indonesia. Rice is one of five commodities that is target of self-sufficiency of Indonesia in period 2010 to 2014, and the surplus target of 10 million tons in 2014 (Kementan, 2011). It is required both short and long term planning to meet rice self-sufficiency.

A variety of agricultural information, especially the cultivated area, growth and yield of major crops, is an important basis to make food policy and economic planning for a economy. Therefore appropriate methods are needed to obtain accurate information to support policy makers for deciding a better agricultural development and planning. The needs of information for agricultural monitoring has identified, such as distinguish, identify and measure the areas of paddy ad other important crops in Indonesia, estimate production early in the year, check the validity of farmers' applications for subsidies. The primary information need for expenditure control is to determine before harvest time what a farmer is growing, in order to predict yields, anticipate the market and estimate the support needed. There is a major time constraint in that the relevant information has to be gathered in the period between crop emergence and crop harvesting, which is just a few months.

At present, crop acreage, production and other agricultural information released by National Bureau of Statistics of Indonesia are mainly obtained in two ways: the traditional overall report (summary of several administrative levels) and the directory sampling based on classical statistics (ubinan).

However, regular survey and monitoring methods are difficult to offer accurate information. The existing sample survey methods based on traditional overall report and directory sampling are easily impact by people and lack of spatial distribution, which can't meet the requirements of information society any more. Low cost agricultural information in time to meet agricultural production and management needs. Remote sensing can obtain surface information spatially, wide area covered, periodicity, and economically. Preliminary result on rice crops extent is at least 75%, of rice yieldestimation model was found to be promising in accuracy with deviation 10-15% from actual yield, there is need to refine the yield and analyzing of remote sensing data. It has many advantages in agricultural monitoring and survey.

This paper presents an overview of present status of remote sensing technology used for operational agricultural crop monitoring and examines some recent use in Indonesia. It also reviews various remote sensing data based studies to map paddy field area and estimate rice yield in Indonesia.

II. TRADITIONAL METHODS FOR CROP AND RICE PLANTED AREA AND YIELD ESTIMATION

The main sources used of food crops data collection in Indonesia is through Agricultural Survey (SP) and Survey of "Ubinan" (sampling area of 2.5 m by 2.5 m). Productivity data collected from survey of "Ubinan" used Sub-S questionnaire conducted by officers of Local Agriculture institution and Sub- District Statistics Coordinator. The schedule of "Ubinan" survey adjusted to harvest time. The survey questionnaire used for Ubinan called SUB-S. There are two types of questionnaires are used: SP-PADI to gather extensive information about the rice plant, and SP-crops to gather extensive information on crops. This information is collected monthly from every district in Indonesia. "Ubinan" Data of productivity is collected through a sample survey of households by applying direct measurement approach on the selected plot of sampling area ("Ubinan") and farmers interviews to get information of productivity characteristics such as use of fertilizers, seeds, irrigation, pesticides, how to planting, and so forth.

Complete SP data collection carries out through sub-districts area approach. Data of paddy and secondary crops planted area are estimated using a block system of irrigation, farmers report, the number of seeds used, and Eye Estimate based on total area of paddy field. Data Collection Method: Information relating to planting area, area damaged (puso), and harvested area are collected through Agriculture Survey conducted by officers from the Agriculture Local Institution.

III. THE USED OF RS AND GIS FOR CROP MONITORING IN INDONESIA

Satellite remote sensing data provide valuable information on two important crops parameters i.e. crop growth and crop discrimination. The multi temporal satellite data both optical and SAR, are hopefully potential for monitoring paddy planted area and its yield estimation. Therefore, developing standardized and faster methodology with sufficient accuracy on the assessment of agricultural landuse (mainly on paddy field) and rice yield estimation model is prime need in the near future. Current status of the use of remote sensing and GIS for paddy field monitoring in Indonesia as follows:

3.1. Rice Field Mapping

The accurate information of crop planted acreage can be obtained if data of paddy field area used as base information for calculation is correct. Most of existing paddy field data published by some agencies is in tabular form and significantly diffrent from each other, series of data are not similar, availability of data is not complete. These problems caused base map used is different; most of map used is in small scale. Therefore it is not sufficient for analysis and planning. Spatial data of paddy field in detailed scale detail is needed for basic analysis and estimation.

Since 2010, Agriculture Land Mapping Program Using Satellite Image has been done by Ministry of Agriculture. Very high resolution satelite image (<= 1m, such as IKONOS, GeoEye, QuickBird, and WorldView) has been used for agricultural land inventory and mapping. This program also includes Agriculture Local Institution for field verification and updating of the data analysis results by using the GPS. Base map of paddy fields of Java and Madura Island has been done by Center of Agricultural Data and Information System in year 2010 (Pusdatin, 2011). Bali, Nusa Tenggara, Maluku Islands, Prov. of North Sulawesi and Gorontalo is done by Ditjen Agriculture Infrastructure and Facility in year 2011 - 2012.

3.2. Paddy Field Monitoring

Based on rainfall data of BMKG, IAARD has developed maps of drought and flood vulnerability, while LAPAN has used MTSAT data. The condition of vegetation greenness level of paddy field derived from MODIS and TRMM also have been provided for crop monitoring (Figure 2).

3.3. Integrated Cropping Calendar

Another GIS application used to support food security program and anticipate variability and change of climate that is uncertain and unpredictable is Integrated Cropping Calendar. It has been developed by Indonesian Agency of Agricultural Research and Development (IAARD) specifically to support National Rice Production Enhancement Program (P2BN) and generally food security program in an effort to deal with climate variability and change.

Cropping calendar map and table are used as a guide for stakeholders, extension, and farmers to determine time of planting food crops, with recommendation of varieties, and fertilizer. It contains a map that illustrates potential of cropping patterns and planting time for crops, especially rice paddy field, based on potential and dynamics of climate and water resources. This map provides information of time of planting, total area planted in each season in each district. Factual analysis performed using weather data forecasts from Agency of Meteorology, Climatology, and Geophysics (BMKG). Other information resources used are Potential Availability of Water (PU, PJT, Research and Development Agency); existing planting area and patterns (BPS, DG TP, DG PSP, MoA); floods, drought, pests (DG TP, DG PSP, MoA, BPTPH); and Innovation and technology recommendations (IAARD and Universities). The Integrated

Dynamic Cropping Calendar can be run online in http://katam.info/main.aspx. Figure 3 shows Cropping Calender Map of Indramayu Dustrict, West Java Province of Indonesia.

3.4. Paddy Planted Area and Yield Estimation

Indonesian Center for Agricultural Land Resources Research and Development (ICALRD) - IAARD of Ministry of Agriculture (MoA) has conducted joined research on estimation of paddy planted area yield with some national (LAPAN, IPB, BPPT, PUSDATIN - MoA, etc) and international institutions (JAXA - RESTEC, JIRCAS of Japan, IRRI of Philippines, GIC - AIT of Thailand, etc). Various remote sensing data both Optic and SAR have been used for this research, such as MODIS, Landsat TM, JERS OPT and SAR, ALOS AVNIR-2 and PALSAR, RADARSAT. Beside that, Hyper spectral and UAV technologies also are examined to be other alternative for paddy planted area and yield estimation. The analysis result of paddy planted area that presented by paddy growing stage condition shows in Figure 4.
MoA has planned to implement operationally use of satellite data for crop monitoring and yield estimation. It is needed warranty of data availability and continuity. Data should be easy to obtain and meet the conditions of agricultural land in Indonesia.

IV. FUTURE OUTLOOK

For some time, Indonesia's food security program was based on a food availability approach with twin strategies: price stability and rice self-sufficiency. Recently the government implemented the sustainable food security paradigm (SFSP) with four primary dimensions (Simatupang, 1999, in Rusastra et al., 2008): availability, accessibility, vulnerability (stability and reliability), and sustainability. Monitoring and early warning systems is one of inherent components in the implementation of the paradigm.
On the other hand, satellite data have multiple benefits. It can provide multi concepts information, i.e. spatial, temporal, spectral, sensor, polarization, and stage. Thus remote sensing technology also can produce agricultural information, such as crop condition, as well as crop production information. Information of agriculture area condition and distribution of crop planted and harvested, especially paddy is essential for planning and management of food security, water resource, and agricultural production facility. Paired of those components can be used to develop National Information System of Agricultural Land Resources and Crops for Strengthening Food Security in Indonesia (Figure 5).

V. CLOSING REMARKS

Multi concepts remote Sensing data and technology is very useful for crop monitoring, and yield estimation of Indonesia that has a large area of agriculture. By combining with ground data, it can produce better information for policy making. The National Information System of Agricultural Land Resources and Crops for Strengthening Food Security in Indonesia is need to be developed. However, the warranty of data availability, continuity, and its suitability is also needed.

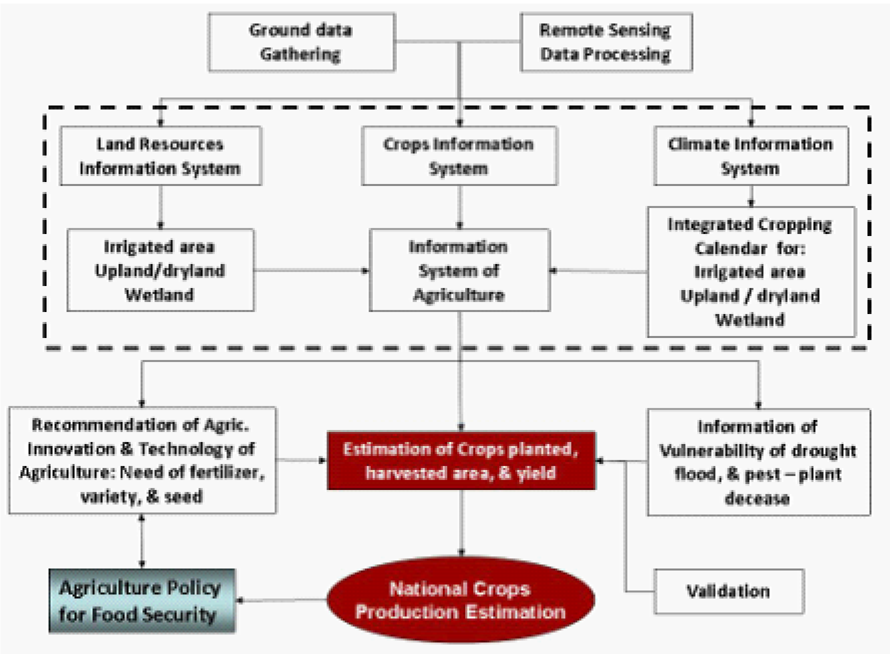


Figure 5. National information system of Agricultural Land Resources and Crops (Food, Estate, and Horticulture Crops)

REFERENCES

[1]BPPT. 2012. Model prediksi padi berbasis data hyperspectral dan MODIS. Agency of Assessment and Application Technology. Presented at Kick-Off Meeting of Rice Production Estimation Using Satellite Data. Bogor, 14 June.

[2]Harian , K. 2012. Potensi tanam padi bisa capai 3,96 juta hektar. PelitaOnline.com. Last retrieval 20 July.

[3]Irianto, G. 2011. Ketersediaan lahan pertanian dan air untuk mencapai kedaulatan pangan. Directorate General of Agriculture Infrastructure and Facility of MoA.

[4]Kementan. 2011. Arahan menteri pertanian pada retreat kementerian pertanian. presented at retreat ministry of Agriculture of Republic of Indonesia, Ciawi, 28 January.

[5]LAPAN. 2010. Potential drought monitoring over agriculture area in Java Island, Indonesia. Progress report of SAFE Prototype Year 2010. Presented in Meeting with Agricultural Dept and JAXA at LAPAN Oct 14.

[6]Pusdatin. 2012. Koordinasi dan sinkronisasi data luas baku lahan sawah dan luas panen padi mendukung pembangunan pertanian. Center of Data and Agricultural System Information of MoA. Presented in Meeting Coordination and Sincronization of Paddy Field Data, Jakarta, 17 April.

[7]Pusdatin. 2011. Agriculture land mapping program using satellite image (Java Island 2010). Center of Data and Agricultural System Information of MoA. Presented in Satellite Application For Environment (SAFE) Meeting: "Agricultural Project Using Satellite Technology In Indonesia", Jakarta, 8 September.

[8]Rusastra, I. W. T. A. ,Napitupulu, R. Bourgeois. 2008. The impact of support for imports on food security in indonesia. Economic and Social Commission for Asia and The Pacific. United Nation. New York.

[9]Shofiyati, R.I.H., Ismullah, H. Pawita. 2011. Multi sensor satellite data for rice production estimation in an effort to support national food security. J. Agric. Food. Tech., 1(12) 238-244: 238 – 244.

Agricultural Monitoring by Earth Observation Satellite

Kei Oyoshi and Shinich Sobue
Earth Observation Research Center, Japan Aerospace Exploration Agency Tsukuba Space Center, 2-1-1 Sengen, Tsukuba, Ibaraki, 305-8505, Japan;
E-mail: ohyoshi.kei@jaxa.jp

1. INTRODUCTION

Food security is a critical issue for the international community. In June 2011, the meeting of G20 agriculture ministers was held to discuss global food security and they agreed on an "Action Plan on Food Price Volatility and Agriculture"[1]. This plan includes a Global Geo-Agricultural Monitoring (GLAM) initiative utilizing remote sensing to improve projections of crop production and weather forecasting. Hence, satellite remote sensing is expected to contribute national, regional and global food security through the systematic and efficient collection of food security related information such as agro-meteorological condition, crop growth or yield estimation. Food security related information is utilized to take mitigation strategies or policies to manage food shortages or trading, and ensure food security. Especially in Asia, rice is the most important cereal crop because Asian countries are responsible for approximately 90% of the world rice productions and consumptions. There- fore, Asian countries are expected to contribute GLAM through the construction of rice crop monitoring system.

JAXA has been developing and operating Earth observation (EO) satellites, and researching and promoting application of EO data to agriculture. This paper presents the overview of our activities for food security including the estimation of rice production, the crop phenology monitoring, and the development of a drought early warning system.

2. AGRICULTURAL MONITORING SYSTEM

2.1. Rice Crop Yield Monitoring

JAXA is working with the Thailand Geo-informatics and Space Technology Development Agency (GISTDA) to develop a prototype system designed to provide paddy rice area and yield estimation. Generally, crop yield estimation consists of two components, estimation of cultivated area and yield per area. The Cultivated areas of paddy field are detected by the seasonal pattern of SAR data over paddy field. This means paddy field is filled with water just before planting, then covered by dense vegetation in growing season. Figure 1 shows the overview of paddy field mapping by using phenological characteristics of paddy rice. In this research, the paddy filed map was derived from the seasonal Advanced Land Observation Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) data with a simple thresholding method.

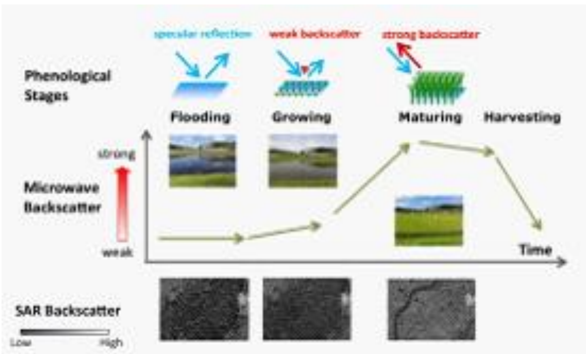


Figure 1. Seasonal changes of backscattering coefficients over paddy field.

Table 1. Results of rice yield estimation of the study site located in Khon Kaen, Thailand. Validation data of yield per unit (YPU) shows average YPU of direct seeding area and that of transplanting area.

	Acreage(m^2)	Yield per Unit(g/m^2)	Yield(t)
Estimation	164.406	203.96	33.53
Validation	166.766	230/280	40.96
Accuracy	98.6%		81.9%

Then, to estimate rice yield per unit, we applied a rice crop model developed by Khon Kaen

University, which is a simple and convenient model. The input data to the model are physical and chemical properties of the soil, physiological crop characteristics, and daily weather such as photosynthetic active radiation, precipitation, wind velocity and humidity. Some of these parameters were acquired by satellite observations and others are by in-situ measurements. Table 1 shows the result of rice yield estimation of the pilot study area. The results are highly consistent with the validation data of in-situ measurements and the accuracy of paddy acreage and rice yield are 98.6% and 81.9%, respectively. Now, we are trying to expand the prototype system to whole Thailand.

2.2. *Crop Phenology Monitoring*

The prototype system to estimate rice yield have been developed only for the small pilot area. To expand the system to the whole economy for national food security and statistics, crop calendar which means the timing of planting, growing and harvesting of each area is needed to estimate yield per area. The Asian region has a large variety of the crop calendar such as single or double and sometimes triple cropping and the pattern is mostly relies on the water availability. Since growing cycle highly affects the rice yield, it is imperative to identify growing cycle for rice yield estimates.

High revisit frequencies of EO data like MODIS are useful for identifying crop calendar. Figure 2 shows time- series NDVI of Chao Phraya River Basin in Thailand, the growing cycle of P1 (double cropping) is differ from that of P2 (triple cropping). The crop calendar is utilized for the determination of the observation timing with higher resolution data or the crop model to estimate rice yield.

2.3. *Drought Early Warning System*

Drought is a main cause for natural disaster to damage crop production. Many Asian countries are suffered from severe droughts because decrease in rice production affects food security and economy. Furthermore, multiple effects of climatological oscillation such as El Nino and climate change can strengthen drought damages. Hence, drought early warning information is quite valuable for food security policy or decision makers to take proper actions in order to prevent or mitigate food insecurity and economic damages.

Satellite-based drought index (satellite-based KBDI : Keetch-Byram Drought Index) was developed by the University of Tokyo and JAXA. This index is calculated from precipitation and Land Surface Temperature (LST) data to consider water supply by rainfall and surface evaporation. To generate KDBI, Global Satellite Map for Precipitation (GSMaP) that indicates hourly status of accumulated rainfall of each 10km gridded area and LST derived from Japanese Geostationary Meteorological Satellite (MTSAT: Multi-functional Transport Satellite) data are used. The index indicates drought condition of each 10km grid and the index is updated on a daily basis. Figure 3 illustrates KBDI in February and August over the Figure 3. Satellite-based drought index over the Asia-Oceania region. Seasonal differences due to the Asian monsoon effects in Southeastern Asia are distinctly captured by KBDI.Asia-Pacific region, KBDI can identify and quantify the drought conditions seasonally and spatially. In February, KBDI indicate dry conditions over Thailand, Myanmar, Laos, and India, these countries are in dry season because of the Asian monsoon effect. On the other hand, KBDI indicate dry conditions over Java, Indonesia in August.

2.4. *Agro-meteorological Monitoring*

Agro-meteorological variables such as precipitation, PAR, LST or soil moisture are significant for crop yield estimation and early warning, because these are significant parameters for controlling crop growth. JAXA provides these agro- meteorological data including Global Satellite Mapping of Precipitation (GSMaP) derived from multiple microwave radiometer and RADAR satellites [2], PAR, LST, soil moisture and snow cover extent [3] via the internet for public use.

3. CONCLUDING REMARKS

This paper presents JAXA’s activities for application of space-based technology to agriculture and food security areas. Space-based technology is useful to get information about yield estimates, crop and agro-meteorological conditions. By developing the algorithms and the systems for agricultural monitoring, we would like to contribute to ensure food security in the Asia-Pacific region, especially for Asian rice crop monitoring in cooperation with Asian countries. And also, this will be useful input for GEO-GLAM initiative from the Asian region.

REFERENCES

[1] http://un-foodsecurity.org/node/1115

[2] http://sharaku.eorc.jaxa.jp/GSMaP/index.htm

[3] http://kuroshio.eorc.jaxa.jp/JASMES/index.html

Monitoring of Paddy Rice Planting Using MODIS Data: Asian Perspectives

Satoshi UCHIDA Srisaang KOAJARERN, Ekkarat PRE
Social Sciences Division,
Japan International Research Center for Agricultural Sciences (JIRCAS)
Ohwashi 1-1, Tsukuba, Ibaraki 305-8686, Japan;
Tel: +81-29-838-6614; Fax. +81-29-838-6614
E-mail: uchidas@jircas.affrc.go.jp

***Abstract*-The author carried out studies for the purpose of monitoring paddy rice planted area in provincial scale by using MODIS data for the cases of different climatic condition in Asia. One case was for Heilongjiang Province in P.R. China located in cold temperate climate zone, where rice was planted once a year in limited period of summer season. The other case was for Java Island in Indonesia located in tropical humid climate zone, where rice could be planted through the year in condition that available water was sufficient. In Heilongjiang's case study, the author developed a method to estimate fractional percentage of paddy field per pixel with 250 meters resolution and to produce a map of paddy field for whole province. Formula of estimation of fractional percentage was constructed by using geometrical relation appeared in two dimensional scattergram of NDVI, Normalized Difference Vegetation Index, and NDSI, Normalized Difference Soil Index, which was calculated from Band 1 and Band 7 of MODIS data. Here, a few scenes of cloudless MODIS data were selected in the period of transplanting rice and combined them to remove effect of cloud coverage. This method was only applicable to specific case as that all the paddy rice in target area was transplanted within limited period and it was inundated with water at certain time. The result showed topographic features of location of existing paddy field and also depicted spatial pattern of expansion of paddy field appeared dramatically in around 2007. In Java's case study, on the other hand, the author attempted to develop a method of identifying paddy rice planted time by employment of 16-day composite data. Paddy rice planted time was discriminated by using time-series EVI, Enhanced Vegetation Index, and NDWI, Normalized Difference Water Index, calculated from Band 1 and Band 7 of MODIS data. This method estimated at a unit of pixel with 250 meters resolution, so that a pixel comprised with portions of rice planted in different time might not be estimated rice planted time properly. Although this constraint was not negligible in considerable part of Java, it was successful to depict spatial pattern of paddy rice planted time for continuous years from 2000 to 2011 for whole Java and to show areas where rice planted time was altered due to variation of rainfall. Result of the former case study suggests that estimation of acreage of paddy rice planted area using MODIS data would be conditionally possible depending on level of mixture of different stage of growth of paddy rice in a pixel. However, the latter case study indicated promising possibility of monitoring of paddy rice planted time in provincial scale using MODIS data for any part of Asia and Pacific region.**

Keywords-Paddy Rice;Planting Pattern;Monitoring; MODIS;Asia

1. INTRODUCTION

Rice is one of most significant staple food crop especially in Asian region. Rice was cultivated in more than two thousand years ago in Southern and Eastern part of Asia and paddy rice field has been extended in the region. According to FAO statistics data in 2010, China was the world largest rice production economy and its ratio to the world total production was 29.3 percents. The second largest was India and the third largest was Indonesia, then summation of rice production of top three countries occupied 57.2 percents of the world total, and the following rice production countries were Bangladesh, Vietnam, Myanmar, Thailand and Philippines. As we recognized, all these countries are located in Asian region and mostly in tropical humid climate zone. This climate condition could be suitable for growth of rice in general but it is noted that rice is cultivated also in cold temperate climate condition. A northernmost rice cultivating area in China is Heihe in Heilongjiang Province, of which latitude is 50 degrees and annual averaged temperature is -0.3 degree in Celsius. This area has suitably high temperature for growing rice in summer season. By this fact, we should be noticed that rice cultivating areas were spread over trans-climatic conditions.

There are various types of cropping pattern on paddy fields existed under wide range of climatic conditions. Growth of rice requires adequate accumulated temperature, so that cultivating period of paddy rice in high latitude zone would be limited in short summer season. Under such condition, planting and harvesting time of rice are generally harmonized with adjoining fields. On the other hand, in tropical humid climate region, which is major rice producing area, rice could be cultivated through the year and time of rice planting is somewhat associated with supply of water to paddy field. If irrigation network is well constructed, rice planting time would be followed by a schedule which was designed to distribute water to irrigation blocs one after another. In this condition, rice planting could be recognized as pattern of spatial transition by unit of irrigation blocs. However, if irrigation network is not well constructed or localized, rice planting time might not be harmonized with adjoining fields. Actually, it can be observed a situation that different growth stages of rice, i.e. transplanting, growing, harvesting, are presented simultaneously at the same location, for example in Java Island of Indonesia.

Monitoring of time and acreage of planted or harvested rice especially for wide area has been expected as one of promising subjects of satellite remote sensing application. However, it is difficult subject to be realized due to existence of complex cropping pattern, of which planting time and even number of cropping time per year cannot be consolidated in some cases. For the purpose of discrimination of rice planting using satellite remote sensing data, we usually detect specific pattern of surface condition of paddy fields that is combination of inundation by water when transplanting rice and vegetation growth after transplanting. This discrimination can be performed in condition that a set of data observed in appropriate time is provided. If the objective area is wide and cropping season is not uniform over the site, required data should be temporally continuous or sampled by certain intervals. At this, a number of researches were conducted to adopt spatially coarse resolution but temporally high resolution data such as MODIS, Moderate-resolution Imaging Spectroradiometer, which was presently the most popular data to produce land cover/use dataset in global scale. This high temporal resolution, say daily, could mitigate effect of cloud cover which was disadvantageous characteristics of optical sensor data by way of composition of multi-temporal data or smoothing of temporal change.

Xiao et al. (2002) showed possible discrimination of paddy rice field from other non-flooded agricultural fields such as wheat in landscape scales using 10-day composite SPOT/VEGETATION data. They introduced indices representing flooded condition as well as vegetation condition and discriminated paddy rice field by pattern of temporal changes of these indices. Their group extended similar concept to apply to MODIS data and produced paddy rice distribution map for southern China (Xiao et al. (2005)) and South and Southeast Asia (Xiao et al. (2006)). Gumma et al. (2011) attempted to estimate rice areas by analyzing seasonal changing pattern of NDVI of MODIS for South Asia and obtained good correlation with statistics data for specific year. Sakamoto et al. (2005) analyzed time-series MODIS data to detect phenology of paddy rice in Japan and applied this technique to Mekong Delta for identifying cropping system mainly on paddy rice (Sakamoto et al. (2006)). Yearly changes of paddy rice cropping were also analyzed using MODIS data for Mekong Delta (Sakamoto et al. (2009)) and Po River in Italia (Boschetti et al. (2009)).

The author also carried out researches on development of method of monitoring paddy rice planting in provincial scale using MODIS data for cases in Asian region. One case for Heilongjiang Province of P. R. China located in cold temperate climate zone, where rice was planted once a year in limited period of summer season (Uchida (2006, 2008)). The other case was for Java Island in Indonesia located in tropical humid climate zone, where rice could be planted through the year in condition that available water was sufficient (Uchida (2010)). Climatic conditions and also cropping patterns of rice in these case study sites were contrastive and therefore method employed to each case was developed independently. In this article, he describes methodology and result of these case studies from view point of adaptability of MODIS data and discusses about perspectives of monitoring paddy rice planting using MODIS data for Asian region.

2. CASE STUDY FOR HEILONGJIANG PROVINCE OF P. R. CHINA

2.1 Study Site

The study area, Heilongjiang Province, is located in the northeastern part of China, and is one of the major food grain crop production areas of China. It is also notable that the northernmost paddy fields in China are located in this Province. In the central part, the Songhua River runs from west to east, and the major rice production areas are located along this river and its tributaries. About 20% of the total area of the Province is used for agricultural land and 15% of this agricultural land is paddy fields. Figure 1 shows the trend of sown area of major crops cultivated in the Heilongjiang Province since 1980. As shown in the figure, sown area of rice had increased gradually before the middle of 1990s and then after that turned to high rate of increase. We indicated that the change of sown area of wheat showed opposite tendency to that of rice and supposed that considerable parts of paddy field expanded in this period were converted from wheat field.

Climatic conditions are too cold to permit the cultivation of crops in winter, but it is normally warm enough to cultivate rice as well as soybeans and maize in the summer. Since adequate temperatures for growing rice tend to be recorded over a rather short period, the time of cultivation of rice does not differ much from place to place in the Province. Table 1 shows yearly changes of the earliest and latest date of transplanting rice among ten observation points in the Province.

Generally, rice is seeded in the middle of April and transplanted in late May, then harvested in late September. Because of the variation in meteorological conditions year by year, damage to rice production due to low temperatures happens in some years. The reason for the cultivation of rice under somewhat marginal environmental conditions is that the quality is high and fetches good prices in this region. As a result, more and more land has been exploited for paddy fields, even in recent years.

Table 1 Earliest and latest rice transplanting date among ten observation points in the Heilongjiang Province

Year	Earliest	Latest
1999	May 18	June 2
2000	May 15	June 4
2001	May 16	June 2
2002	May 12	June 2
2003	May 14	June 4
2004	May 18	June 2

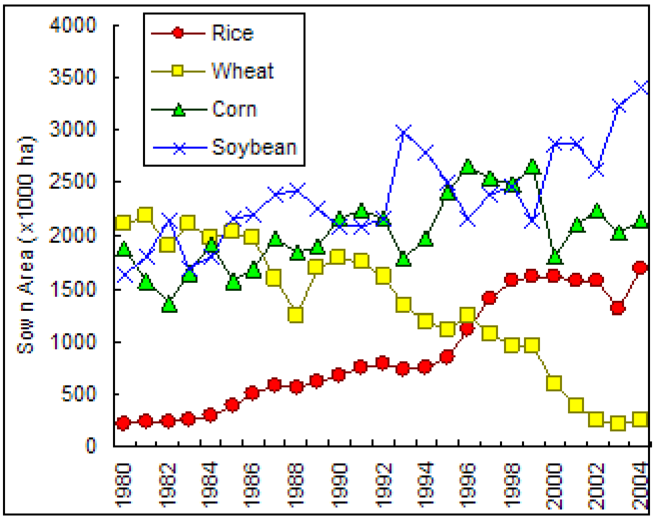


Figure 1 Trend of sown area of major crops in the Heilongjiang Province

Source: Heilongjiang Statistical Yearbook-2005

2.2 Data and Method

MODIS data was provided by the SIDaB (Satellite Image Database) operated by the Agriculture, Forestry and Fisheries Research Information Center. Another set of satellite data used in this study was LANDSAT-TM, ETM+ data acquired in the season from late in May to early in June. Almost all the paddy fields were inundated by water at the time of observation of these satellite data, when the cultivation of rice was at the transplanting stage. For the MODIS data, I examined the cloud cover conditions during the rice transplanting period for the year from 2003 to 2008, and selected cloudless scenes. I then extracted an area 1000 km west to east (4000 columns) and 900 km north to south (3600 lines), which covered all the rice production areas of the Heilongjiang Province, with a pixel size of 250 meters on the UTM geographical coordinate system.

From late in May to middle in June, land cover condition of paddy field is mixture of inundation by water and a little vegetation, and that of upland field was almost bare soil. Therefore, a pixel data of MODIS in this period is generally mixed by three components of land cover, i.e. water body including mixture with a little vegetation, bare soil and forest. Part of water body should be mostly identical to paddy field if permanent water body such as lakes is removed. By this consideration, a model to estimate fractional ratio of paddy field per pixel of MODIS was developed through estimation of fractional ratio of water body per pixel by means of formula mentioned bellow.

I selected cloudless scenes but the completely cloud-free condition over the whole area of the Heilongjiang Province could not be expected. Then, the following processes were taken in order to remove the effects of cloud coverage as well as haze. Firstly, cloud-covered area was extracted by using ISODATA classification for each selected scene and secondly, buffer zone, of which the width was 10 pixels outside the cloud-covered area, would be involved. This treatment aimed at exclusion of shadow part of cloud from band data used for estimating the area of paddy field. Then extracted cloud area was given a value of 1 for all bands. Lastly, by comparing the value of Band 1 among selected cloudless scenes, the minimum value would set as representative at the pixel and other band data obtained at the same time also used for the process of estimation.

In the next step, 2 types of indices: NDVI (Normalized Difference Vegetation Index) and NDSI (Normalized Difference Soil Index) were calculated.

$$NDVI = \frac{B2 - B1}{B2 + B1}, \qquad NDSI = \frac{B7 - B1}{B7 + B1},$$

where B1 to B7 denotes the band values converted to the reflectance at the upper atmospheric layer. The bandwidth of B1, B2 and B7 are 620-670, 841-876 and 2105-2155 nanometers, respectively. For the scenes taken in the period of transplanting rice, both NDVI and NDSI of paddy field were supposed to show rather low values. On the other hand, those of bare soils of which a considerable part would be upland cropping field were to show low in NDVI and high in NDSI and those of forest were to show high in NDVI and low in NDSI.

Figure 2 is a scattergram of NDVI along the horizontal axis, and NDSI in the vertical. The pure pixels of densely vegetated area were concentrated around an NDVI of 0.73 and an NDSI of 0.05. Another concentrated cluster of distribution could be found around an NDVI of 0.25 and an NDSI of 0.42, which corresponded to pixels of bare soil areas. I examined the allocation of points in the scattergram in consideration of the fractional ratio of paddy fields per pixel. In the end, it was clear that pixels with a higher fractional ratio of paddy tended to be allocated closer to the lower left corner of the triangle formed by the points.

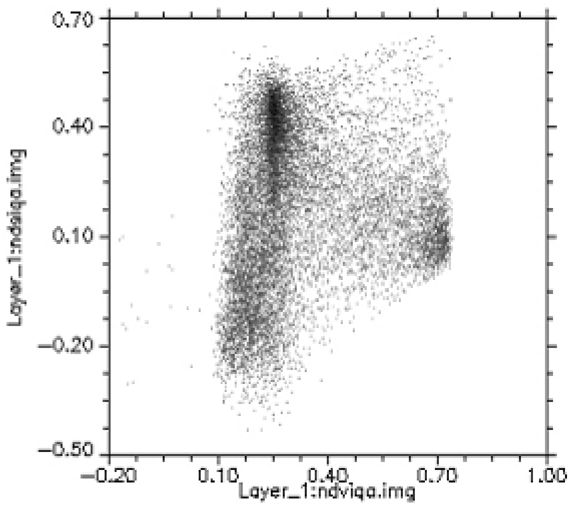


Figure 2 Scattergram of NDVI and NDSI calculated from MODIS data

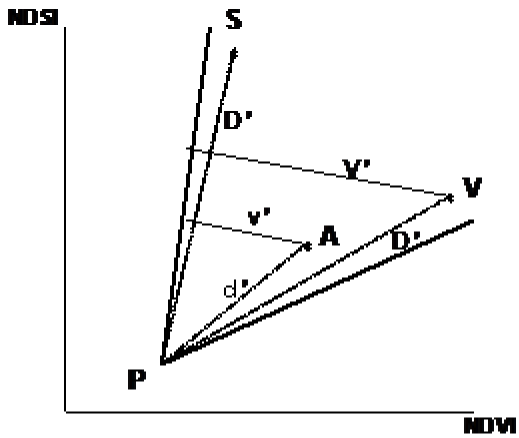


Figure 3 Schematic representation of obtaining parameters used in the estimation models

To construct a formula for estimating the area of paddy fields, several types of parameters defined in the scattergram were investigated. Figure 3 schematically represents the expression of 2 types of parameters. One is termed Normalized Distance (ND) in this paper, which was defined by the following procedures. First, I drew 2 sets of enveloping lines outside the point-distributed parts along the non-vegetation end and non-bare soil end, and the crossing point of the lines was set as P. Next, I identified the center of pure pixels of densely vegetated areas as V and the center for bare soils as S. The conversion ratio to the Y axis could be obtained so as to have the same distance (D') from P to S as P to V. By using the same conversion ratio, a distance from P to an arbitrary point in Figure (A) would be assigned as d'. Thus, the form of ND could be defined as follows.

$$ND = \frac{d'}{D'}.$$

Another parameter is provisionally called the Paddy Index (PI) in this paper. This index was obtained by using the distance from the enveloping line of clusters at the far side from V to the point V, which would be represented as V' and from the same line to the point A, which would be represented as v'. The form was defined as follows.

$$PI = (1 - \frac{v'}{V'}) \times (1 - ND)$$

PI was expected to show a positive correlation with the area of paddy fields in a pixel accordingto the considerations mentioned above. To confirm this expectation, I modified the referenced data of distribution of paddy fields derived from LANDSAT-ETM+ to level sliced data with an interval of 10 % of fractional paddy field area in a window with a size of 9 pixels by 9 pixels, and then examined the relationship between the mean value of sliced data and PI defined above. The relationship between PI and the area of paddy field per pixel is shown in Figure 4. This figure exhibits an evident correlation, and the coefficient of determination of fitting to the formula shows a sufficiently high value with a range from 0.9898 to 0.9996.

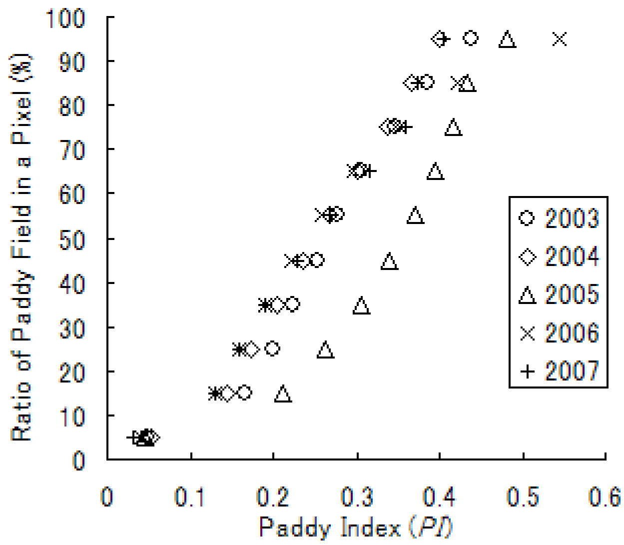


Figure 4 Relation between Paddy Index (PI) and ratio of paddy field per pixel

2.3 Result

I estimated the distribution of paddy fields in Qingan County and its surroundings as example by applying the formula shown in the previous section. Figure 5 shows a comparison of the estimated area of paddy fields using different methods: (a)classification using LANDSAT-ETM+ data, (b)pixel-based classification using MODIS data, and (c) fractional estimation using PI. The total area of paddy fields in this area was 116,960 ha, based on the result of classification of LANDSAT-ETM+ data, whereas the area by pixel-based classification applied to MODIS data was about 40 % underestimated. For the case of estimation using PI, the result was underestimated by 1.98 % compared to the reference data. The spatial pattern of distribution of paddy fields shown in (c) generally matched that in (a).

Although the general pattern of distribution of paddy fields was satisfactorily reproduced by the method using PI, which was compatible to the pattern drawn in (c), the estimated value might not be accurate in some areas. I then examined the characteristics of locations where the values were considerably overestimated or underestimated. A typical overestimation occurred in the middle of extensively developed paddy fields. Actually, this kind of area consisted not only of paddy fields but also facilities or infrastructures such as roads, canals, and buildings. However, the spectral reflectance of these materials that contributed to the pixel value of MODIS could be rather complex and might not be optimally distinguished from paddy fields. On the other hand, a typical underestimation was found in areas comprising small-scale paddy fields surrounded by bare land. This was assumed to be caused by the specification of MODIS where the spatial resolution of Band 7 was 500 meters, so NDSI with a pixel size of 250 meters could not appropriately represent the condition of mixed bare soil and paddy fields.

Figure 6 shows the values of paddy field area by County estimated from two different sources, one was MODIS data in 2003 and the other was LANDSAT-ETM+ data (Path:117, Row:27-29) obtained May 31, 2003. Counties listed in legend of the figure were overlapped area in both source data. This figure indicates generally good correlation between two values especially in the range of high values. However, in the range of low values, the amount from MODIS data tended to be underestimated. These Counties comprised comparatively smaller ratio of paddy field, which was located largely along narrow valley area, and this condition of distribution of paddy field was assumed to be a cause of underestimation.

Figure 7 shows paddy field distribution of Heilongjiang Province estimated by the method mentioned above for years from 2005 to 2008, where lines in the figure means boundary of County. In this figure, northern part of the Province was cut off because no paddy field existed there. Then, Figure 8 represents location of paddy field, which was extracted as more than 10 percents of fractional ratio of paddy per pixel in either 2006 or 2007. In this figure, part of paddy field is overlapped on digital elevation data. From these figures, spatial distribution of paddy field in Heilongjiang Province and its temporal change could be characterized as follows. First, paddy field existed mainly along major tributaries of Songhua River, which runs from west to east in the middle part of Province, and there was a little portion of paddy field near from Songhua River. Elevation range of location of paddy was generally 100 to 200 meters above sea level. Another area comprising considerable part of paddy field was Sanjiang Plain located eastern side of the Province. For this area, elevation range of location of paddy was generally 60 to 70 meters above sea level. Secondly, increase of area of paddy field was remarkable in 2007. This happened especially in Sanjiang Plain.

3. CASE STUDY FOR JAVA ISLAND OF INDONESIA

3.1 Study Site

The study site is Java Island and adjoining Madura Island of East Java Province, of which total acreage is 127 thousand square kilometers and population was 136.61 million in 2010. This is the most intensive rice producing area in Indonesia and annual production of rice in this area was 33.47 million tons from 5.91 million hectares of harvested area according to statistics data by Central Statistics Bureau of Indonesia (http://www.bps.go.id/). Geographically, the site is located between 105 and 115 degrees of east longitude and between 6 and 9 degrees of south latitude as shown in Figure 9. Topographically,

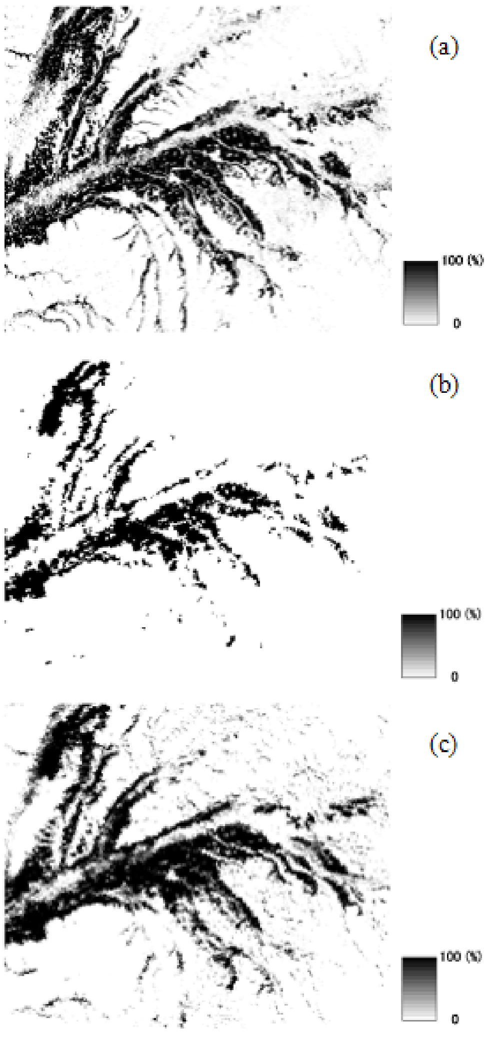


Figure 5 Comparison of distribution of paddy area; (a) classification of LANDSAT-ETM+, (b) pixel based classification of MODIS, (c) fractional estimation of MODIS

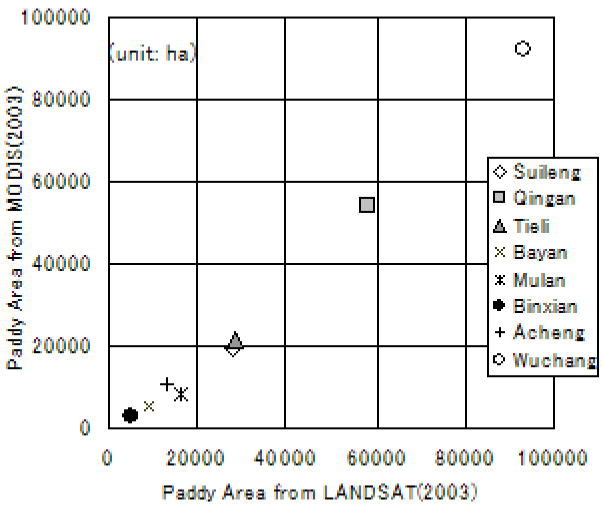


Figure 6 Comparison of paddy field area between the values estimated from LANDSAT and MODIS (2003)

alluvial plains are presented along parts of coastal area and a number of mountains, of which peak elevation are more or less 3,000 meters, exist along middle part of the island. Annual rainfall has wide spatial variation, i.e. from less than 1,000 to more than 4,000 millimeters, and generally it shows higher amount around mountains. Temperature is high enough to grow rice through the year except part of high altitude, say more than 1,500 meters, so that rice could be cultivated at any season if water was supplied sufficiently. Paddy field distribution is also shown in Figure 9 expressed by using gray tone. This paddy distribution data was produced by means of manual interpretation of LANDSAT-ETM+ imagery by National Mapping Agency of Indonesia.

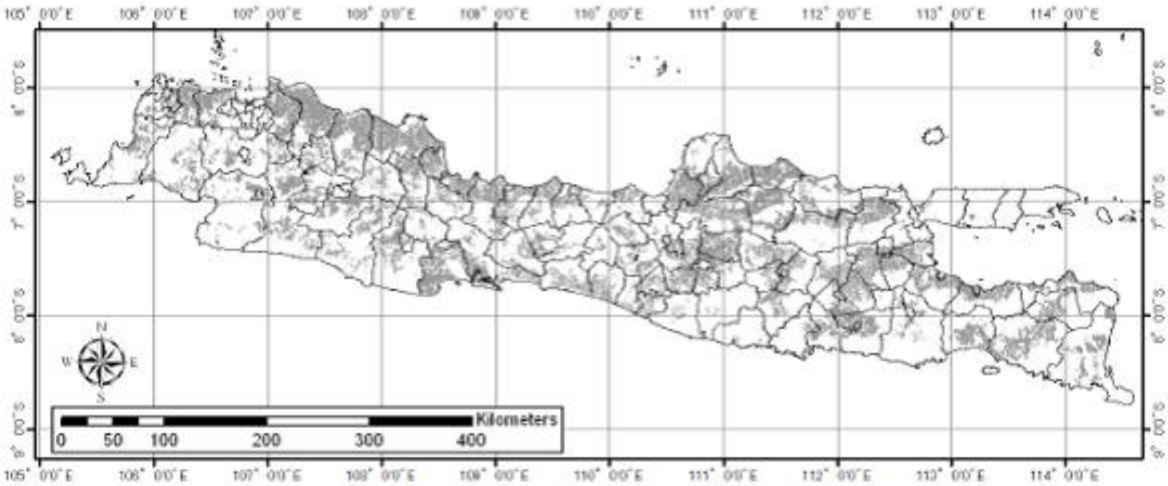


Figure 9 Map of study site overlapped with paddy field represented by gray tone

3.2 Data and Method

In this case study, I aimed at analysis of variation of paddy rice planted time of the site, where rice planted time might be changed year by year, using MODIS data. MODIS data employed here was Vegetation Indices 16-day Global 250 m product (MOD13Q1), and data in tiles assigned h28v9 and h29v9 downloaded from the site ftp://e4ftl01.cr.usgs.gov/MODIS_Composite/MOLT/MOD13Q1.005/. MOD13Q1 contains EVI (Enhanced Vegetation Index), NDVI (Normalized Difference Vegetation Index) and reflectance values of Band 1, 2, 3 and 7 of MODIS data. Then in this study, additional index, NDWI (Normalized Difference Water Index), which represented surface condition whether covered by water or not, was calculated by following equation.

$$NDWI = \frac{B1 - B7}{B1 + B7},$$

where Bi is reflectance value of band i of MODIS

data.
Preliminary examination indicated that the maximum of NDWI was appeared at time of transplanting paddy rice and EVI was sharply increased after the time of transplanting. Then I analyzed relation between paddy rice planted time which was obtained from statistical information compiled at a local agricultural office and temporal changes of NDWI and EVI. As a result, I constructed a flow of estimating time of planting rice as shown in Figure 10. In this figure, “Paddy mask” was a data of paddy field distribution displayed in Figure 9.
Estimation of rice planted time was verified by comparison with statistics data. Statistics data of monthly planted area of rice by Sub-District as a unit were obtained from agricultural offices of a few Districts in West Java Province. I selected statistics data of Ciranjang Sub-District of Cianjur District, because rice was planted twice per year and each planting period was concentrated in around one month for whole area. For other areas, rice planting period was to be diversified and it was difficult to employ statistics data for the purpose of comparison. Figure 11 shows relation between values of ratio of rice planted area to area of paddy field according to statistics in horizontal axis and values of ratio of rice planted area estimated by using MODIS data to area of paddy field calculated from map data in vertical axis. This figure shows good correlation between two components so that estimated time was supposed to be generally matched with actual planted time. It also should be noticed that estimated area was smaller to actual acreage. This implies that not all the rice planted area could be discriminated its planting time properly and thus accurate estimation of acreage of rice planted area would not be possible by the method introduced here.

3.3 Result

Planting time of paddy rice in Java has been varied both spatially and temporally even for area where large scale irrigation network was constructed. Figure 12 represents sample site of Karawang District in West Java Province, where irrigated paddy field is extensively presented on alluvial plain. Figure 13 shows temporal changes of rice planted area by Sub-District for year of 2005 to 2006 and 2006 to 2007. Horizontal axis of this figure denotes numbers of 16-day unit started from January 1 and vertical axis denotes ratio of rice planted area to area of paddy field in Sub-District. In the year 2005 to 2006, when the rainfall condition was normal, a cascade feature of rice planted area from upper stream to lower stream was clearly represented. However, in the year 2006 to 2007, when the rainfall was much less than normal, it could be recognized that the rice planted time tended to be late in the lower part.
Figure 14 depicts distribution of first rice planted time averaged for the period from 2000/2001 to 2010/11. At this, first rice planted time was defined as the first occurrence since September, because rainy season as well as cropping calendar generally started around October. This figure shows spatial transition pattern of rice planted area associated with progress of time as that from inland to northward in the northwestern coastal area, where large scale irrigation system was constructed. Another area equipped with large scale irrigation system was located in northern central coastal part and it showed earlier rice planted time. In inland part, of which water was supplied by more or less local scaled irrigation system, rice planted time tended to be heterogeneously distributed.
Figure 15 shows distribution of standard deviation of first rice planted time for the same period as Figure 14. Averaged standard deviation value for the whole site was calculated as 45 days and the higher value was presented around marginal part of large scale irrigation system or inland area. This figure indicates that time of planting rice could be varied in a range of more than one month for most of paddy field in the site.
Figure 16 shows yearly trend of deviation of date of rice planted time from averaged value. It is recognized from the figure that planted time was varied distinctively year by year. One probable factor to make shift of date of rice planted time was pattern of rainfall, then I analyzed monthly rainfall at 10 observation points and characterized that 2000, 2001, 2002, 2004, 2006 and 2009 were less than normal amount of rainfall for the period from September to December and rest of years were more than normal. By using this feature of rainfall, correlation between planted time of rice and rainfall amount was examined by the following method. If rice planted time for specific year was earlier than average, parameter set as -1 and if it was earlier more than 32 days, set as -2. Conversely, if rice planted time was later than average, it set as +1 and +2 for the case of later more than 32 days. Multiplication of this parameter by factor on rainfall pattern of each year, i.e. +1 for more amount of rain and -1 for less amount of rain, was summed for all the year. Figure 17 represents the correlation between first rice planted time and rainfall that a part displayed in bluish color tended to be delay of rice planted time in case of more amount of rainfall and a part in reddish color tended to be delayed of rice planted time in case of less amount of rainfall. In the figure, redden parts are generally presented at lower part of large scale irrigation network and at foot of mountains.

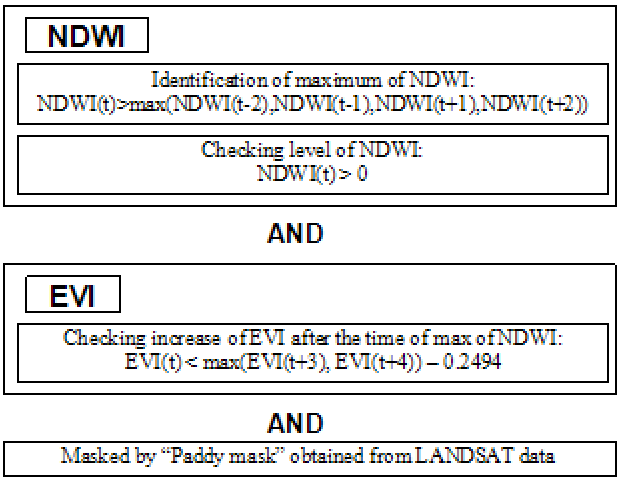


Figure 10 Flow of estimating time of planting paddy rice using MODIS data

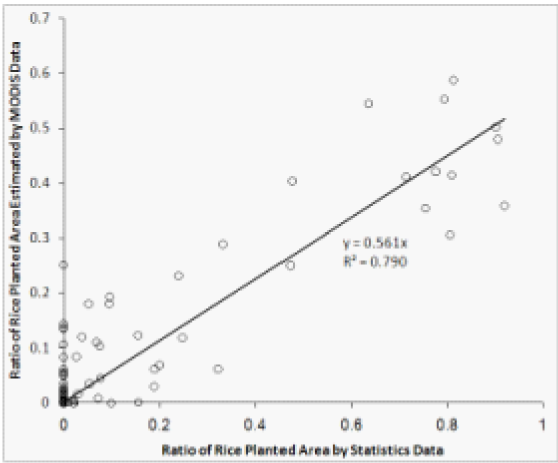


Figure 11 Relation ratio of rice planted area to paddy field between by statistics and estimation by MODIS data

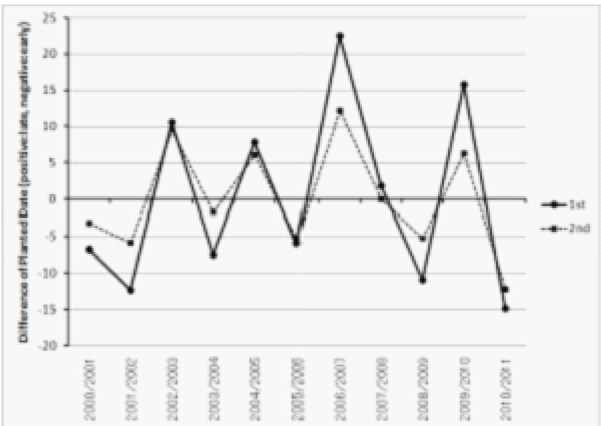


Figure 16 Yearly trend of deviation of date of rice planted time from averaged value

4. DISCUSSION AND CONCLUSION

Results of Heilongjiang's case study described in Chapter 2 suggest that estimation of acreage of paddy field using MODIS data was promising in case of application to Heilongjiang Province of China where cropping season of rice was almost simultaneous for all the site as well that vegetation by other upland crops was negligible at the time of transplanting rice. This is condition of not commonly appeared in Asian region but limitedly presented in a part of cold to temperate climate zone. However, acreage estimation of paddy field employing fractional ratio per pixel using MODIS data was supposed to be possible for wider areas, of which rice was cultivated in same season and transplanted almost simultaneously, because water body as land cover type of transplanting period of paddy field had distinctive reflectance characteristics. Therefore, not only areas in cold to temperate climate zone but also parts of warmer climate or parts located in large scale irrigation system would be potentially targeted to estimate acreage of paddy field using MODIS data.

On the other hand, results of Java's case study described in Chapter 3 suggest that monitoring of paddy rice planted time using MODIS data was promising to be applied to any locations under various climatic conditions. This also contributes to demonstrate spatial distribution of areas prone to fluctuating production of rice due to scarcity or surplus of water. However, there are some limitations to discriminate rice planted time properly for the case that different conditions of growth stage was mixed in a pixel and also to calculate accurately about temporal data of amount of production or even acreage of planted or harvested rice. Remote sensing is not almighty tool to monitor agricultural production but potentially utilizable technology to extract some aspects relating agricultural production. It is, therefore, of importance for users of data on agricultural production processed from remote sensing data to be conscious of limitations or constraints of employed methodology, and also to recognize what data actually means.

REFERENCES

[1]Boschetti, M., Stroppiana, D., Brivio, P.A. and Bocchi, S. ,2009. Multi-year monitoring of rice phenology through time series analysis of MODIS images. International Journal of Remote Sensing, 30, 4643-4662.

[2]Gumma, M.K., Nelson, A., Thenkabail, P.S. ,Singh, A.N. ,2011. Mapping rice areas of South Asia using MODIS multitemporal data. Journal of Applied Remote Sensing, 5, 053547.

[3]Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M, Ishitsuka, N and Ohno, H.,2005. A crop phenology detection method using time-series MODIS data. Remote Sensing of Environment, 96, 366-374.

[4]Sakamoto, T., Nguyen, N.V., Ohno, H., Ishutsuka, N., Yokozawa, M.,2006. Spatio-temporal distribution of rice phenology and cropping systems in the Mekong Delta with special reference to the seasonal water flow of the Mekong and Bassac rivers. Remote Sensing of Environment, 100, 1-16.

[5]Sakamoto, T., Cao, P.V., Kotera, A., Nguyen, K.D. and Yokozawa, M.,2009. Detection of yearly change in farming systems in the Vietnamese Mekong Delta from MODIS time-series imagery. Japan Agricultural Research Quarterly, 43, 173-185.

[6]Uchida, S.,2006. Development of rapid mapping method of paddy fields using satellite data applied to Heilongjiang Province in China. JIRCAS Working Report, 50, 1-7.

[7]Uchida, S.,2008. Development of a method to estimate spatio-temporal distribution of paddy field in the Heilongjiang Province of China using MODIS data. Journal of the Japanese Agricultural Systems Society, 24, 207-215.

[8]Uchida, S.,2010. Monitoring of planting paddy rice with complex cropping pattern in the tropical humid climate region using LANDSAT and MODIS data -A case of West Java, Indonesia-. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, 38, 477-481.

[9]Xiao, X., Boles, S., Frolking, W., Salas, W., Moore III, B. ,Li, C.,2002. Observation of flooding and rice transplanting of paddy rice fields at the site to landscape scales in China using VEGETATION sensor data. International Journal of Remote Sensing, 23, 3009-3022.

[10]Xiao, X., Boles, S., Liu, J., Zhuang, D., Frolking, S., Li, C., Salas, W. and Moore III, B.,2005. Mapping paddy rice agriculture in southern China using multi-temporal MODIS images. Remote Sensing of Environment, 95, 480-492.

[11]Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J.Y., Salas, W.,Moore III, B.,2006. Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sensing of Environment, 100, 95-113.

Use of Remote Sensing and GIS Applications in the Generation of Agricultural Statistics Construction of Sampling Frames

Elar T. Sifuentes Montes

Agronomist. Magister Scientiae in Soils. Ministerio de Agricultura – Oficina de Estudios Económicos y Estadísticos – Unidad de Estadística.

esifuentes@minag.gob.pe, elarsm@gmail.com .

***Abstract*-In order to improve methods of collecting basic statistics of the farmer, the Office of Economic and Statistical Studies (OESS) of the Ministry of Agriculture has proposed the implementation of the National Agricultural Survey using probability sampling methods to ensure the collection and processing of the statistical information, ie, have quantifiable data and a rough measure of the error of sown area, harvested area and volume of agricultural production.To this end, it requires the definition and construction of area frameworks that allow the selection of agricultural samples that are representative and stable over time, which allows to implement surveys to assess changes in agricultural production.This article provides guidance on the methodology to be used to build frameworks area for Coast and Highlands regions of Peru.**

INTRODUCTION

The functions of the Office of Economic and Statistical Studies of the Ministry of Agriculture is the generation of statistical information, reason for which we are implementing the methodology of probability sampling.

Currently, agricultural statistics generation is given by the method of the estimation by the key informants in each statistical sector. The political organization of Peru is made up of Regions, they are comprised by the Provinces and Provinces by Districts. For agricultural statistical reporting purposes each District has been divided into Statistical Sectors with visible and easily identifiable boundaries on the ground. The statistical information of surface, crops and producer prices are collected monthly from the Statistical Sector and these data are added for each level.

Among the activities planned by the OESS, it is expected the implementation of the National Agricultural Survey (NAs) by probabilistic methods through area sampling. It is therefore necessary to construct the sampling frame by using map data, satellite imagery, computer equipment and specialized staff in GIS.

In this regard, the objectives of the activity are contributing to the design and construction of area frame and split the total area investigated (target population or universe) into small sampling units, without overlap or omission.

National Agricultural Survey (ENA)

The ENA has the objective of obtaining estimates of agricultural production variables (planting, harvesting, production) at the national and regional levels in order to generate statistical information with known sampling error margins and confidence intervals based on probability sampling.

To fulfill its objective, it requires a statistical framework. Between the frames that are wanted to build, are the area frameworks of the investigated zone, which do not exist so far and that must be performed in a first stage at the province level.

AREA FRAMEWORK CONSTRUCTION FOR THE COAST AND HIGHLANDS REGIONS

Peru has three clearly defined natural regions: Coast, Highlands and Forest. On the coast intensive irrigated agriculture is done, with high level of technology as it has good quality land and favorable climate, the only major limitation is that only has water in the 51 valleys as a result of the rains on the highlands. In Highlands, agriculture is done with an intermediate to low level of technology, with little use of fertilizers and mostly under rainfed conditions. As for the Forest, the technology used is low, the soils are not very fertile and agriculture is given mostly under rainfed conditions.

The NAS is oriented in a first stage to the Costa and Highlands regions, where the construction of sampling frames have defined characteristics for each region.

For the definition and construction of the area framework area, we must recur to satellite images, aerial photographs, digital geographic information, etc.

GUIDELINES FOR THE CONSTRUCTION OF FRAMEWORKS AREA FOR THE COAST REGION

In the case of the Coast, the construction of the area framework is performed in several phases:

1. Image capture and georeferencing
2. Formation of Strata
3. Conglomerates Formation: With range of sizes for each province
4. Formation of Segments, for areas with smallholdings.

Image Capture and Georeferencing

This activity will require high-resolution satellite images of about 0.60 m to 1.0 m. It makes use of Google Earth Pro images with good resolution and which can identify areas up to 0.60 m resolution.
In this phase, the scenes for a given area is printed from the computer display and then georeferenced each capture using the ARC GIS. Printed images are linked through a mosaic with Erdas in order to obtain a complete picture of the area in which to conduct the research.
Then cadastral digital map data are added with the aim of identifying parcels, agricultural expansion, etc. allowing to improve information of the area to be investigated.

Conformation of Strata

In a first stage the cartographer will identify agricultural and non agricultural areas through visual interpretation and then demarcate areas according to the agricultural use of land, on a scale set by the statistical researcher in order to form homogeneous regions according to the proportion of farmland containing the study area. Stratification is subsequently validated with field work.
The scale is established:

Natural Region	Stratum	Description: The proportion of cultivated land
Coast	10	70% more than the total area
	20	30% to less than 70% of the total surface
	30	Less than 30% of the total surface
	40	Area urban agriculture

In the second stage out field work is carried, which consists of verifying that the stratification on office work corresponds to land use and also identify and define parcels owned or leased by the agricultural enterprises.
In the third phase mapping is updated and the information of the field work is presented for the formation of conglomerates.

CONFORMATION OF CONGLOMERATES

With the information generated in the previous phase, the statistical researcher sets the average parcel size to form conglomerates according to multiplying by 10 the average area of the plots. With these features, the cartographer will proceed to the construction of clusters by grouping the parcels to reach the average size of the clusters.
Once conglomerates are formed by the cartographer, the statistical researcher shall determine the number of samples to be considered for research. In those conglomerates where the number of segments sampled is greater than 10 will proceed to the segmentation.

Segmentation of Conglomerates

This activity will take place in those conglomerates containing more than 10 plots, which occurs in areas where there is much smallholding. 10 plots are grouped to form segments, of which one will be randomly selected as representative of the conglomerate.

METHODOLOGY FOR THE CONSTRUCTION OF AREA FRAMEWORKS HIGHLANDS REGION

In a similar way to the coastal region, the construction of the area framework for the Highlands Region is done in several phases:
1. Image capture and georeferencing
2. Formation of blocks
3. Formation of strata
4. Formation of Primary Sampling Units
5. Formation of Segments

Image Capture and Georeferencing

This activity will require high-resolution satellite images of about 0.60 m to 1.0 m. For this activity images from Google Earth Pro with good resolution will be used and which can identify areas up to 0.60 m resolution.
In this phase, the scene for a given area is captured from the computer screen, then the scene is georeferenced using the ARC GIS. The images are linked through a mosaic with Erdas in order to obtain a complete picture of the area in which to conduct the research. Then, digital map information as political boundaries, location of population centers, contours, etc. are added in order to improve information of the zone to research.

Block and Strata Conformation

For the formation of strata, specialized staff identifies agricultural and nonagricultural areas through visual interpretation, and then makes up blocks on the agricultural area assigning a percentage of agricultural land. With this information the statistical researcher develops a scale of stratification and classifies the stratum according to the content of agricultural land.
The scale set for the Highlands Region is:

Natural Region	Stratum	Description: The proportion of cultivated land
Highlands	Valley floor	Valley floor
	10	70% more than the total area
	20	30% to less than 70% of the total surface
	30	Less than 30% of the total surface

For the formation of Primary Sampling Units in the Highlands, most plots have no cadastral boundaries and land use is not continuous (crop rotation, fallow land, etc.), so they are divided in function of easily recognizable boundaries as streams, rivers, canals, roads, fences and more.
In the case of the valleys, it will form a stratum called "valley floor", as in this area farming is constant because it has different crops to the altitude levels, availability of irrigation, proximity to roads, etc

Conformation of Primary Sampling Units

With the information generated in the previous phase, the statistical researcher sets the average size to form the Primary Sampling Units. With these features, the cartographer proceeds to the construction of the PSUs, which consists in search easily recognizable boundaries on field to reach the average size of the PSUs and form homogeneous regions in the proportion of surface. Stratification will be validated later with fieldwork.
The features that should have a PSU are:
Must include diverse ecological floors characterizing the farming areas of the zone, from the valley floor to the mountains.
Must include plots of the low, intermediate and high lands. Each PSU to its interior comprise between 4 and 10 segments.
Where possible, each PSU should contain heterogeneous agricultural areas that are under irrigated and rainfed.
Identify and define the inter-Andean valley, which is called "Valley Floor" as a special stratum.

PSU Segmentation

Once formed the PSUs in the entire field of the agricultural area of study, the statistical researcher shall determine the number of samples to be considered for research.
Selected the samples of PSUs, the cartographer performs the segmentation of them in order to form homogeneous areas and that these are representative of the stratum assigned and can be attended by the surveyor during the survey.
Following the work done in office, a field work is done both on the Coast and on the Highlands, which consists of verifying stratification corresponds to land use and that the boundaries of conglomerates, PSUs and segments are clearly recognizable on the field. It also identifies the plots owned or leased by the agricultural enterprises.
After the field work, mapping that had been done previously is updated and the updated information is presented for the Implementation of the National Agricultural Survey.

CONCLUSIONS

Each Natural Region of the economy has unique characteristics, so that the construction of the area frameworks must be adapted to each of them.
The final results of NAS on crops, crop yields and volumes of production differ in relation to the intensity of each crop, since many crops are produced in the economy. The coefficients of variability are lower in the most representative crops.
The cost of the area framework construction is high, because it requires updated cartographic materials as high-resolution images. The optimal dates for making satellite images do not necessarily coincide with those of major agricultural activity. Similarly, the field work consumes much of the budget.

Crop and Pest Modeling in a Climate Change Context

Henry Juarez
Universidad Nacional Mayor de San Marcos
henryjuarezsoto@gmail.com

Thanks for all organizers for the invitation to take part on the Workshop on the application of Remote Sensing and GIS on Crops Productivity among APEC Economies. I will base my presentation on farmer's perception and how they have seen the effects of climate change in their valleys and explain it from a GIS and modeling point of view.

Lino Mamani is a Papa Arariwa (potato guardian) in the Sacaca farming community near Pisac, in the Peruvian Andes. He and others in five neighboring communities have established a 12,000 hectare potato park where they cultivate and conserve Andean potato cultivars. Says Mamani, "In the old days, the rain came at the right time, the land was very fertile, and the sun used to shine in the right amount. Now we see that the sun is hotter, and the rains do not come at the right time. We have hailstorms, freezing temperatures, and droughts like we have never seen before. There is also an increase in insect pests and diseases. The potato cultivars that our grandfathers grew down by the river are now moving higher up the mountain slopes. In this land, we have our Apu [sacred mountains] around us, which help our potatoes and the other crops and animals grow. Once there was snow on those mountains, now they look sad, because the climate is getting warmer, and there is no more snow. Other species and animals are suffering, including the condor, foxes, deer, ducks, and fish that have always lived with us and are very dear to us. We know that Pacha Mama (Mother Earth) is not happy with all these changes, and we have to work together to make her happy again."

The potato is a traditional crop grown by smallholder farmers in the central Andes. A staple of the Peruvian diet, the potato was first domesticated about 8,000 years ago. The central and southern Peruvian Andes are the richest area of potato biodiversity in the world. Many methods were used to analyze the effect of climate change on potato cultivation, and pest and disease estimation.

a)Participatory mapping:

Participatory community mapping projects was implemented to gather grassroots information about biodiversity conservation and local farming practices. Participatory community mapping has relied on in-depth field-level mapping, focus group meetings, and interviews with families from highland communities of the departments of Cusco, Huancavelica, and Junín (Peru).

Detailed mapping was conducted and farmers were asked to identify their potato fields on high resolution maps of the community area. Fields were assigned a numerical identifier so that data could be attached to them. The owners of each plot were asked a series of questions to reconstruct the recent history of field level management: cultivars grown, type of tillage, rotation design, etc.

Although areas of improved cultivars are proportionally growing fastest at extremely high altitudes, between 3,900 and 4,350 meters, overall cultivation intensity and fallowing periods are inversely related to altitude. However, smallholder farmers continue to cultivate widely dispersed fields in order to minimize the risk of losing an entire crop to disease or other factors in the high-risk mountain environment. The negative effect of Climate Change on potatoes in the Andes was a surprise finding. Geographic Information System mapping reveal that farmers have ascended the Andes 150 meters during the past 30 years to escape agricultural diseases and pests due to increased temperatures. It's expected that by 2050 there will be no higher ground to escape to.

b)Pest and disease modeling

Climate change presents new challenges for pest management. A major challenge is anticipating the effects of new climate scenarios on plant pests. In contrast to evaluations of, for example, the effects of new climate scenarios on plant physiology, pests involve at least two species interactions.

Given the sensitivity of potato late blight to weather conditions, there is little doubt that a wetter and warmer environment will present new challenges to potato farmers in Peru. The actual need of fungicides to control late blight in north Peru (Cajamarca, La Libertad & Huanuco) is estimated in US$29.4 million. It is expected that fungicide use will increase by an additional US$2.1 million due to climate change. Native potato production zones (over 3,000 masl) are the regions that are most at risk. It is estimated that additional expenditure on fungicides in these areas will increase by US$1.3 million per cropping season. This means that more than 60% of the cost of the additional fungicide needed to control late blight will have to be assumed by the poorest farmers due to climate change.

In the case of insects, there is a significant increase of 48% more areas affected by tuber moth of potato. The threshold (more than 3 generations/year of Phthorimaea operculella) is currently affecting 31,145 ha (11.7% of total area of potato). It is expected that this threshold will increase up to 45,317 ha due to climate change. As tuber moth is reported along the coast and warm inter-Andean valleys, it is expected that climate change will also affect slightly the native potato-production zones.

Under this context, the economy should assist low-input potato farmers develop adaptation strategies to meet these challenges to reduce the risk associated with pests and diseases through: i) improvement of tools to study the pests and diseases in the context of climate change, ii) adoption of the most resistant cultivars into farmers' fields, iii) improvement of farmers' capacities to control pests, and iv) development of integrated management strategies of crop protection.

CONCLUSIONS:

Data from the participatory mapping and pest and disease modeling allow scientists to develop an understanding of patterns of cultivation in the Andean highlands. Regarding climate change, the question now isn't about when we'll be affected because it's already happening. The new question is how we can adapt to the effects of climate change. Maps provide material for researchers to draw conclusions about the effects of external phenomena, such as market forces and climate change, on traditional cultivation methods and cultivar portfolios. The data are not only useful to farmers as they plan their cultivation, but also to scientists throughout the world who are studying the biodiversity and sustainability of this modest, yet precious agricultural resource.

Application of Remote Sensing and GIS Technology on Crops Productivity in the Philippines

Esteban C. Godilano, Ph.D.[1] and Xerxees Remorozo[2]

1. Space Technology Expert and Senior Technical Adviser on Climate Change. Office of the Under Secretary for Policy and Planning. Department of Agriculture. Elliptical Road, Diliman, Quezon City 1100, Philippines;

2. Information Systems Analyst. Management Information Division - Field Operations Service. Department of Agriculture. Office of the Secretary. Elliptical Road, Diliman, Quezon City 1100, Philippines

sgodilano@yahoo.com , xremz@yahoo.com

***Abstract*-Efficiency in the agricultural sector especially in crop monitoring and forecasting can be augmented effectively by using Information Technology tools such as Remote Sensing, Global Positioning System and Geographic Information System, collectively called geospatial technology which have greatly advanced and continued to advance in the developed world. In developing countries however, especially in the Philippines the conventional method of crop monitoring involves ground surveys conducted by Bureau of Agricultural Statistics every semester to estimate crop acreage and production at the provincial and national level. We believed that geospatial technology offers an effective alternative to conventional method of crop area determination and yield estimation. This contention was demonstrated in a research study conducted the International Rice Research Institute and Philippine Rice Research Institute using active and passive remote sensing imagery. Remotely sensed satellite observations were able to provide non-political, objective and timely area and production estimates.**

The purpose of this paper is to present the Philippine initiatives and experience in crop yield measurement, outline some of the problems we have encountered in our attempt to employ geospatial technology in our work as researchers and development workers in government. In doing so, we provide some recommendations to alleviate if not totally minimize the said constraints. We hope that present and future users of the technology shall be least affected by such problems so that mapping of our land and the resources found therein can be done more efficiently and effectively.

To conclude, history shows that most of the benefits of any new technology go to the early adapters and those who are adopting new tools and are innovative enough to adapt the tools locally. Using geospatial technology as a planning and measuring tool in agriculture and natural resources is expected to follow the same pattern. Today, geospatial technology is no longer a luxury for the academe, scientist, and policy makers; it now becomes a necessity for effective and efficient governance.

1. INTRODUCTION

Ideally, agriculture and natural resource management is in need of state-of-the-art tools and procedures to effectively put into practice well-planned integrated and anticipatory strategies of all concerned sectors, government organizations (GOs), peoples organizations (POs) and non government organizations (NGOs). Such calls the use of Remote Sensing (RS), Geographic Information Systems (GIS) [RS is the art and science of making measurements of the earth using sensors on airplanes or satellites. These sensors collect data in the form of images and provide specialized capabilities for manipulating, analysing, and visualizing those images. Remote sensed imagery is integrated within a GIS which is a computer system that can create, edit, store, analyze, visualize data and particularly reveal relationships among features, their patterns, and trends.(http://kb.iu.edu/data/anhs.html)], and Global Positioning System (GPS) [GPS is a space-based satellite navigation system that provides location and time information in all weather, anywhere on or near the Earth, where there is an unobstructed line of sight to four or more GPS satellites. It is maintained by the United States government and is freely accessible to anyone with a GPS receiver. (http://en.wikipedia.org/wiki/Global_Positioning_System)] collectively called geospatial technology. Geospatial technology has long been realized globally as useful tools in collecting, analysing and reporting information about the earth’s resources. With the recent advances in information and communication technology (ICT), these become essential tools that improved the planning and implementation of development projects. Both RS and GIS provide complementary capabilities on the exploration, assessment monitoring and analysis of vegetation and land cover mapping.

In the Philippines, the integrated use of RS/GIS/GPS methods and technologies in gathering, storing, monitoring, and analyzing data and information for natural resources and environmental planning, development, and management, becomes fully mature in the 90s when most of our local researchers and academic institutions have taken advantage of the power of geospatial technology (Reyes, T. Jr. 2009). This however, did not expand on the use of geospatial technology in calculating crop area and production. These technologies can be used to monitor and evaluate agricultural systems to determine where and when rice is grown and where crops are performing well or where they are not. Mapping and monitoring of the biophysical and socioeconomic characteristics of crop production areas is key for developing effective targeting strategies for the dissemination of new technologies and sustainable crop management and diversification options.

Specifically, remote sensing provides a great deal of fundamental information relating spectral reflectance and thermal remittance properties of soils and crops to their agronomic and biophysical characteristics at scales that may range from small patches within a field to large regions. This makes it an attractive tool for site-specific decisions in many environments, particularly with regards to soil characterization, non-destructive monitoring of plant growth and detection of environmental stresses which may limit crop productivity. Key developments in recent years include rapidly increasing availability of remote sensing technologies and substantial improvements of the spatial and spectral resolution. Remote sensing-based technology targeting has an enormous potential to increase the efficiency of technology transfer and impact assessment.

In developed economies, geospatial technology is increasingly utilized in agricultural survey and crop production estimation. In developing countries however, especially in the Philippines the conventional method of rice monitoring involves ground surveys conducted by Bureau of Agricultural Statistics (BAS) every semester to estimate the rice acreage and production at the provincial and national level (http://bas.gov.ph/). According to Jiao et. al., (2006) it has been quite difficult for this method to obtain timely and accurate rice area data although a field-based census can provide statistical estimates, the slow and infrequent collection of data acts as a barrier for timely decision-making. Additionally, this method fails to provide reliable data on the spatial distribution of crops. We believed that geospatial technology offers an effective alternative to conventional method of crop area determination and yield estimation.

The purpose of this paper is to present the Philippine initiatives and experience in crop yield measurement, outline some of the problems we have encountered in our attempt to employ geospatial technology in our work as researchers and development workers in government. In doing so, we provide some recommendations to alleviate if not totally minimize the said constraints. We hope that present and future users of the technology shall be least affected by such problems so that mapping of our land and the resources found therein can be done more efficiently and effectively.

2. THE PHILIPPINE FOOD STAPLE SUFFICIENCY PROGRAM

Globally, food supply is threatened by a growing demand to feed an increasing population in the face of scarcity in land and water resources. Since a majority of small Filipino farmers and rural households depend on farming for their own consumption and income, government support is critical to encourage domestic production or self-sufficiency to address poverty, food insecurity, and providing a key ingredient to economic stability in the long term and likewise addressing the new normal which is climate change.

Rice is the staple food of the Filipinos. It is a politically sensitive commodity with which supply disruption causes people distress. Rice production however, is outstripped by demands. The Philippines was once the biggest rice importer in the world. Rice imports for 2010 is 2.4M tons but was reduced to 500,000 tons in 2011 (www.da.gov.ph). The Philippines consumes about 33,000 tons of rice daily. Approximately, 80% of the total population spends almost 1/4 of their income on rice alone. An average Filipino diet is based on rice. It provides half of our calorie requirements and one-third of our protein intake. Rice accounts for 20% of food expenditures for average households, which increases to 30% for households belonging to the bottom third of our society. Rice is grown in some 3.2 million hectares (more or less) of land, providing livelihood to more than two million households engaged in rice-based farming, along with millions of farm workers, and tens of thousands of merchants and traders. Rice also plays important macroeconomic and developmental roles. Movements in the price of rice have a substantial bearing on overall inflation rates, fuelling concern from policymakers on pricing and fiscal stability. Because a large part of the population remains in agriculture, growth in output and productivity are essential to spur economic development. It is towards these ends that the National Rice Program plays an important role in the flagship food program of the administration of President Benigno S. Aquino III.

The Agri-Pinoy Rice Program is one of the banner components of the Department of Agriculture (DA) mainly concerned in rice farming and uplifting the lives of Filipino farmers. Guided by the principles of the Agrikulturang Pilipino (Agri-Pinoy) framework, the national rice program integrates government initiatives and interventions for the agriculture sector, namely: food security and self-sufficiency, sustainable resource management, support services from farm to table, and broad-based local partnerships. The Agri-Pinoy rice program plays a key role in the Food Staples Sufficiency Program (FSSP), the central focus of the economy's food security policy from 2011 to 2016 and beyond. The FSSP aims to achieve self-sufficiency in food staples. Self-sufficiency means satisfying domestic requirements for food, seeds, processing, and feeds through domestic production. The three key strategies are concentrated in the following: (1) raising farmers' productivity and competitiveness, (2) enhancing economic incentives and enabling mechanisms, and (3) managing food staples consumption (www.da.gov.ph).

3. CURRENT TECHNOLOGY IN MONITORING CROP AREA AND PRODUCTION

The Philippines agricultural statistical system is by and large defined by the plans and programs of the BAS, a staff bureau of the DA. Forecast on paddy rice and corn are directly obtained from the regular production surveys that the BAS conducts on a quarterly basis. The survey instrument contains questions items to cover forecasts for the first quarter after the reference quarter for the estimates. The forecasts of the second quarter after the reference quarter are based on the planting intentions of the farmers. To assist the DA in the monitoring of its development programs/activities for cereal, the BAS has been tasked to generate monthly production indicators of these staple crops. The BAS Provincial Operations Centers (POC) across the economy conducts field observations and accomplishes the monthly rice and corn situation report during the off-survey months. This enables the Bureau to update the survey- based forecasts using the monthly field reports on stages of crop production (Lizarondo, M.S. 2010). In fact, agricultural survey is a backbone of planning and allocation of the limited resources to different sectors of the economy. The basic problems in this survey are: (1) reliability of data, (2) cost and benefits, (3) timeliness, (4) incomplete sample frame and sample size, (5) methods of sampling area selection, (6) measurement of area, (7) non sampling errors, (8) gap in geographical coverage, and (9) non availability of statistics at disaggregated level.

3.1 Remote Sensing and its importance in agricultural survey

Remote sensing is a means to get the reliable information about an object without being in physical contact with the object. It is on the observation of an object by a device separated from it by some distance utilizing the characteristics response of different objects to emissions in the electromagnetic energy is measured in a number of spectral bands for the purpose of identification of the object (Estes, E. and W. Leslie 1974). Satellite data provides the actual synoptic view of large area at a time, which is not possible from conventional survey methods. The process of data acquisition and analysis is very fast through GIS as compared to conventional methods. In addition, satellite data were frequently more timely and reliable, and often more complete, than conventional sources. Remote Sensing techniques have a unique capability of recording data in visible as well as invisible (i.e. ultraviolet, reflected infrared, thermal infrared and microwave etc.) part of electromagnetic spectrum. In so doing, certain phenomenon, which cannot be seen by human eye, can be observed through remote sensing techniques, e.g., agricultural crops which are affected by disease, or insect attack can be detected by remote sensing techniques much before human eyes can see them (Godilano, E. C. an J. Bennet. 2004).

4. THE PHILIPPINE GEOSAPTIAL TECHNOLOGY INITIATIVE

Remote sensing has potential not only in identifying crop classes but also in the estimation of crop area and yield. The examination of the relationships between vegetation indices and yield has been frequently studied over the years and has been shown useful for yield prediction purposes. For example, Major et al (1986) have shown usefulness of some vegetative indices (VIs) to estimate some leaf area index (LAI), biomass and grain production for cereals from radiometric measurements. Tucker et al (1980) found a strong relationship between specific spectral data and yield. The resulting plots of spectral data against time give a distinctive pattern which when integrated could be related to yield. All these relationships have a high correlation with yield. In another study, Green and Invins (1985) also proved that VIs relate strongly to biomass, and have been found to relate directly to yield. Rudoff and Batista (1990), have indicated that spectral data when transformed into VIs have great potential to be used in wheat yield prediction models in tropical regions.

4.1 Farming from the sky

In the last decade, the use of remotely sensed data has proven very effective in gathering a wide variety of crop growth data around the world.

Knowing where and when agricultural crops are planted are key pieces of information that can be use in area estimation and production calculations. Remotely sensed images from satellite platforms that pass over the entire Asian region daily can provide accurate and timely estimates of how much land is planted to rice and when it is planted. There are however, two major sources of imagery that can be use in this measurement, the passive and active sensors[Active remote sensing transmits energy to allow an image to be formed. Active systems direct a bean of energy at a surface and analyze the energy reflected back. An example of active sensing would be RADAR. In the active RS cloud cover is not an issue or night coverage. Passive remote sensing collects energy reflected or emitted from a surface. Passive systems are pretty much what the eyes see, and it's like a photograph. Passive sensing radiates visible light. Cloud cover is a big drawback in passive remote sensing. Satellite orbit is sun synchronous]. In the Philippines, these two sources were used in estimating rice area and productivity in both rainfed and irrigated ecosystems.

Using Passive Sensor

The International Rice Research Institute (IRRI) uses passive sensor in rice monitoring. The advent of free and frequent imagery such as that provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) carried aboard NASA's Terra and Aqua satellites is giving researchers a new point of view. Terra orbits Earth from north to south across the equator in the morning, while Aqua moves south to north over the equator in the afternoon. Thus, Terra MODIS, launched on 18 December 1999, and Aqua MODIS, launched on 4 May 2002, are scanning the surface of the entire planet every 1 to 2 days. This allows IRRI and its partners to continuously map and monitor the rice-growing areas across all of Asia (www.irri.org).

IRRI uses on-the-ground observations to identify the time and duration of key stages of the paddy rice crop, such as flooding, transplanting, heading, and harvesting. The MODIS images that are most suitable for rice mapping are available every 8 days, or 46 times a year, so it can correlate the observed stages of the rice crop to this time series of surface reflectance. This provides IRRI researchers with a paddy rice signature. Any pixel in the remote-sensing image that matches that signature is classified as paddy rice, which results in a map of where and when rice is planted. IRRI scientist however, recognize that MODIS[The instruments capture data in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm and at varying spatial resolutions (2 bands at 250 m, 5 bands at 500 m and 29 bands at 1 km). http://en.wikipedia.org/wiki/Moderate-Resolution_Imaging_Spectroradiometer]imagery is not detailed enough to detect individual paddy fields, but rice is often grown in larger homogeneous areas made up of many adjacent paddy fields, and it is these areas that are depicted (Francis A., and A. Nelson, 2012).

Using Active Sensor

It has been argued that since most rice production in South East Asia occurs under monsoon conditions, an optical-based system such MODIS cannot be used, even during 'dry seasons' where skies are often covered with haze and high-level clouds. The unique capabilities of Synthetic Aperture Radar (SAR) to penetrate clouds, haze, and darkness allows for efficient and timely data collection, which is useful for applications such as rice crop monitoring. Paddy rice, in particular, is an excellent target for SAR as the radar interaction with the ground is simplified due to the flooded surface, and thus, there is a lack of direct soil surface scattering. Spectral reflectance from the water reduces one of the elements in the total backscatter of the target. Researchers focused on assessing optimal temporal data sets based on the dynamic growth cycle of paddy rice, as well as studying the usefulness of these data for determining rice crop acreage.

RAdio Detection and Ranging (RADAR) sensors have the potential to monitor rice plant growth regardless of cloud cover. RADAR backscatter is primarily sensitive to the plant's total biomass, its moisture content and the plant's geometry, and grain yield may only be an indirect effect of these parameters. Irrigated or flooded rice fields show a very characteristic RADAR backscattering signature. In RADAR imagery, rice fields appear very dark during the flooded vegetative phase, and turn brighter during the reproductive and ripening phase. RADAR data is therefore particularly suitable for both rice area estimates and crop growth monitoring.(http://earth.esa.int/applications/datautil/SARDOCS/spaceborne/Radar_Applications/Land_Applications/rice_area.htm)

Potential application in agriculture was one of the driving forces that led to the conception and ultimate creation of the "Rice Crop Monitoring" by the RADARSAT program. Primary research has shown that SAR data can be used effectively in applications such as crop and vegetation type determination, crop condition assessment, soil moisture and erosion, and yield forecasting. Mapping and monitoring irrigated rice production is one of the most promising applications for a SAR system. Research conducted by the Philippine Rice Research Institute (Philrice) in 2008 using satellite RADARSAT[Each of RADARSAT seven beam modes offer a different image resolution. The modes include Fine, which covers an •area of 50 km by 50 km (2500 km²) with a resolution of 10 meters; Standard, which covers an area of 100 km by 100 km (10,000 km²) and has a resolution of 30 meters; and ScanSAR wide, which covers a

500 km by 500 km (250,000 km²) area with a resolution of 100 meters. RADARSAT also has the unique ability to direct its beam at different angles.
http://en.wikipedia.org/wiki/RADARSAT-1]images estimated a total rice production area of 188,050 hectares in Nueva Ecija Province during wet season, and a total palay production of 930,847 tons using an average yield of 4.95t/ha., (JC de la Torre and Alosnos, E. 2008). The accuracy was found to be 91%, providing confidence that multi-temporal RADARSAT data is capable of rice monitoring and yield estimation.

From the results of SAR studies it is suggested that rice yield estimations require at least three RADARSAT data acquisitions taken at three stages of crop growth circle. That is: (1) at the end of the seedling development period, (2) in the early differentiation period, and (3) at the beginning of the harvest period. Alternatively, if multi-parameter RADARSAT data is available, only two data acquisitions are required: (1) at the end of the seedling period, and (2) at the beginning of the harvest period.

Based on the promising results of the research mentioned above, SAR is anticipated to be the dominant data source in the tropic and sub-tropical regions and also provide re-visit schedules suitable for agricultural monitoring. Due to this promising result, a partnership program between IRRI and the Philrice on rice monitoring and forecasting system will be developed by combining modern techniques such as satellite-based remote sensing with weather and crop modeling, and econometric modeling. Real-time information on rice production will be estimated using an Internet-based rice information system developed by Sarmap[Sarmap's mission is to build and provide an innovative, sophisticated yet simple remote sensing software product, dedicated to the generation of digital information for a better management and risk assessment of Earth's natural/environmental resources. http://www.sarmap.ch/],a Swiss company engaged in providing and processing high-resolution radar imagery for rice crop monitoring, that would provide more timely and objective data on area and yield. Sarmap is responsible for providing the necessary technical expertise, training, and facilitation of the acquisition of high-resolution radar images from the European Space Agency (ESA). This system consists of two components that make use of geospatial tools technologies. The remote-sensing component comprises a largely automated protocol using multi-date RADAR imagery for mapping and estimating rice area and planting dates. IRRI and PhilRice scientists will jointly conduct data processing, testing, and validation of the products generated. The national network of PhilRice will be used as test sites (http://grisp.irri.org/product-line-5-3).

4.2 The DA Geospatial Initiative

To complement the research work on geospatial technology mentioned above, the DA is currently implementing a 22 million USD project on a "Unified and Enterprise Geospatial Information Systems" (UEGIS). This locally funded project will set up RS/GIS regional laboratories in the 16 DA Regional Field Units (RFUs) and in seven Bureaus/Attached Agencies including BAS. The laboratories will be equipped with "state-of-the-art" hardware and software and complementary staff trained on geospatial technology. Satellite coverage of the Philippines using the eight-band imagery of WorldView-2[WorldView-2 is a commercial Earth observation satellite owned by DigitalGlobe USA. Launched on October 6, 2009, it is the most technologically advanced high resolution satellite ever put into operation with 8-multispectral imaging bands. The sensor provides a high resolution Panchromatic band at 0.46m and eight (8) Multispectral bands at 1.84m; four (4) standard colors (red, green, blue, and near-infrared 1) and four (4) new bands (coastal, yellow, red edge, and near-infrared 2), full-color images for enhanced spectral analysis, mapping and monitoring applications, land-use planning, disaster relief, exploration, defense and intelligence, and visualization and simulation environments. It will expand the possibilities of remotely sensed data for vegetative studies; bathymetric research; supervised and unsupervised classifications; and all other high-end spectral analysis techniques. The imagery will be made available commercially as 0.5m imagery. (http://worldview2.digitalglobe.com/)]from DigitalGlobe, USA is in the process of delivery by the service provider. Coverage will include both coastal and terrestrial environment. The imagery will update the Strategic Agricultural Fisheries Development Zone (SAFDZ) as per mandated by the Agricultural and Fisheries Modernization Act (AFMA) which will then become the basemap for Philippine Agriculture. The project will also address climate change impacts in agriculture (Godilano, 2009).

5. ISSUES AND CONCERNS

The use of geospatial technology activities in the economy is largely uncoordinated and its utilization in measuring crop production remains a research initiative. As a result, agencies concerned with land use planning, like the Department of Environment and Natural Resources (DENR), the Department of Agrarian Reform (DAR), the Department of Local Government (DILG), the Housing and Land Use Regulatory Board (HLURB), the DA, and others have only very minimal sharing of remote sensing and GIS data. In addition, local manpower and expertise in RS and GIS are not enough. This is partly due to the fact that we have very few earth science schools that offer geospatial technology. In our economy, these courses are not considered glamorous. Only few students are attracted to take these disciplines. There is also a fragmented effort on the part of the academe and government institution to have a comprehensive approach in geospatial technology (Reyes, T. Jr. (2009).

At the University of the Philippines at Los Baños (UPLB), Laguna there exists an Environmental Remote Sensing and Geoinformation Laboratory (ERSGL). This is a modest implementation used principally for academic purposes. According to Bantayan et al. (1999), the presence of this laboratory is insignificant in the promotion of RS and GIS in the economy.

At the University of the Philippines at Diliman, Quezon City there is the Institute of Photogrammetry and Geodesy (IPG) at the College of Engineering since 1960. But to delegate the whole responsibility of educating Filipinos on remote sensing and GIS mainly to this institute would surely not be enough. Other institutions would be required in the propagation of RS and GIS technology in the economy.

The National Mapping and Resource Information Authority (NAMRIA) under the umbrella of the DENR surveys and maps the land and water resources of the Philippines. One of its major mandates is to provide both the public and private sectors with mapmaking services as well as geographic and resource information. NAMRIA has its own RS/GIS laboratory but dedicated to forestry and the creation of the economy basemap. It also provides training courses on geospatial technology (http://www.namria.gov.ph/).

There are also some fortunate individuals who from time to time return from abroad with a degree on space technology and others with good training on RS and GIS. On returning, however, their acquired expertise are only wasted due to misplacement, lack of coordination and the paucity of equipment and paraphernalia needed in RS and GIS. Misplacements are partly caused by promotion of the newly trained expert to an administrative position where that expert has no training at all. In other cases, dislocation of expertise results from the reshuffling of personnel on account of political differences and/or ethnic grouping. In any case, the result is wasted training and underutilization of sophisticated RS and GIS hardware and software in key government offices tasked with the mapping of natural and environmental resources in the economy. Further, this results to an irrecoverable loss of time and money at the expense of government (Reyes, T. Jr. 2009). In some instances, these highly trained individuals are pirated by consultancy firms or further seek "greener pasture" in foreign countries.

While research undertaken by IRRI and Philrice clearly established the discrimination between rainfed and irrigated rice ecosystems in image analysis, there is a need to include other agricultural crops in the measurement. Corn for example, also an important commodity in the FSSP should have an established spectral signature. The difficulty however, arises on how to discriminate the spectral signature between white corn and yellow corn as this is distinctly reported in our agricultural statistics (Table 1). In the Philippines, yellow corn is primarily use for livestock feeds while white corn for human consumption.

5.1 Application of RS techniques in ANR

While this paper focuses on the application of RS in crop monitoring and yield forecasting, the technology has many other applications in agriculture and "value adding" should be considered to take advantage of its availability. The specific application of remote sensing techniques can be used for: (1) detection (2) identification (3) measurement, and (4) monitoring of agricultural phenomena. Areas of specific applications to ANR are: (Godilano, E.C. and J. Bennet 2004 and http://www.ncrsjos.org/gis_applications.html).

6. MOVING FORWARD

The Rio Summit 1992 envisaged that RS and GIS have a prominent role in promoting efforts for sustainable development. The agricultural production in the Third World countries is not able to meet the needs of the growing population in these countries.

Table 1. The Philippine Rice and Corn area and volume of production in 2011. (Source: BAS 2012: http://bas.gov.ph/).

Crops	Area Harvested (hectares)	Volume of Production (tons)
Irrigated Rice	3,072,637	12,358,931
Rainfed Rice	1,464,005	4,325,131
Rice Total	4,536,642	16,684,062
White Corn	1,283,701	2,150,222
Yellow Corn	1,260,911	4,820,999
Corn Total	2,544,612	6,971,221

Agriculture

1. Inventory and mapping	7. Early detection of crop diseases
2. Change detection and assessment	8. Food security arrangement
3. Assessment of irrigated land	9. Monitoring of crop conditions including weed, herbicide and fertilizer misapplication.
4. Soil categorization and mapping	10. Farm planning and plot layout
5. Assessment of degraded lands	
6. Land capability/suitability assessment	

Livestock Survey

1. Population determination	3. Disease identification
2. Distribution of animals	4. Types of farm buildings

Water Resources

1. Surface water inventory and ground water targeting	5. Water quality assessment
2. Floodplain delineation	6. Flood monitoring and assessment
3. Wetland inventory and mapping	7. Determination of drainage boundaries
4. Production of hydrological map	8. Watershed mapping

Meteorology

1. Weather forecasting	4. Monitoring of tropical cyclone
2. Studies of climate change	5. Preparation of information required for flight operations
3. Determination of climatological parameters (e.g. rainfall-amount, onset and cessation temperature, wind speed)	6. Desertification studies

Rangeland

1. Rangeland inventory and mapping	4. Wildlife habitat assessment
2. Rangeland monitoring	5. Carrying capacity
3. Wildlife inventory	6. Time of seasonal change

Forest Resources

1. Inventory and mapping of forest land	4. Monitoring of forest conditions; forest fires, disease and damages
2. Assessment of deforestation	5. Timber harvest and reforestation assessment
3. Tree species identification	

This is because of the advantages acquiring from science and technology are not fully exploited and that a holistic approach for development needs to be exercised. If the development of rural area has to sustain a growing economy and ensure ecological balances, an integrated approach is required to make optimal use of land and water resources. The satellite remote sensing applications for agriculture, soil, water and land management have ample scope to prepare an integrated plan for an action program for achieving sustainable development of renewable natural resources (http://www.un.org/geninfo/bp/enviro.html).

On the other hand, most agricultural surveys rely mainly on statistics based on slow, infrequent, and limited ground samplings taken at the grass-roots level at which data are extrapolated on a national scale. Accurate information is indispensable for making policies related to the spatial distribution of crops, water resource management, annual production projections, and market predictions. The major challenge to be tackled in the future is that of making the interpretation process more automatic, generic, and mechanistic rather than relying on empirical, location-specific remote sensing solutions for crop production measurement. The remote sensing techniques have been and it will continue to, a very important factor in the improvement of the present systems of acquiring and generating agricultural data. For example, the United States Department of Agriculture (USDA) has its own Production Estimates Crop Assessment Division (PECAD)[The PECAD is the world's most extensive and longest running (20 years) operational user of commercial satellite data, using numerous satellite platforms to evaluate agronomic situations worldwide. PECAD is the only operational unit of its type in the world. PECAD is responsible for global crop condition analysis and estimates of world grain, oilseed, and cotton production. Satellite remote-sensing data are a critical components used in making crop production and condition estimates for key markets and competitors, providing reliable, repeatable, and comparable observations. In 2001, the division confirmed and enhanced remote-sensing data by incorporating economic, weather, crop model, and field observation data in a "convergence of evidence" methodology. Remote sensing enabled PECAD to obtain information in regions where such information is often difficult to obtain (http://history.nasa.gov/ presrep01/pages/usda.html)] within the Foreign Agricultural Service (FAS) for assessing global agricultural production and conditions that affect world food security. A similar set up could be establish within APEC and hopefully could be part of the outputs of this workshop.

We contend however, that without institutional support the vision of a successful geospatial technology in any government organization will never be met. The following are the considerations for an effective use of geospatial technology: (1) geospatial technology has "organic" elements, (2) good short term and long term strategic planning must occur, (3) it is vital to recognize and account for the different needs of each organization, (4) support from management, and (5) placement of a geospatial resource officer (GRO) in every organization. Illustrated in Figure 1 are the major components of geospatial technology.

Figure 1. Component of geospatial technology

1.GIS technology is of limited value without the people who manage the system and develop plans for applying it to real-world problems. RS/GIS users range from technical specialists who design and maintain the system to those who use it to help them perform their everyday work.

2.Possibly the most important component of geospatial technology is the continuous availability of satellite data and likewise its affordability that would likely determine the choice between active or passive sensors..

3.Methods: a successful geospatial technology operates according to a well-designed plan and business rules, which are the models and operating practices unique to each organization. Methods developed by advance countries should be tailored fit to countries in the tropics where agricultural lands are fragmented and planting dates varies widely.

4. Software provides the functions and tools needed to store, analyze, and display geographic information. The choice of software however, will be constrained by its market price and technical support from developers and/or providers.

5. Hardware is the computer on which geospatial technology operates. Today, RS/GIS software runs on a wide range of hardware types, from centralized computer servers to desktop computers used in stand-alone or networked configurations.

No doubt about it, geospatial technology will cost millions of dollars, not to mention the additional costs for training of staff who will operate these high-tech equipment, but developing countries should go by the principles of cost efficiency, that in the long run, the huge investment will pay off a hundredfold, then we need not think much about our fears and jitters.

In summary, the use of remote sensing technology has been rapidly expanded for the development of key sectors. This paper highlights the fact that the remote sensing techniques will continue to be very important factor in the improvement of present system of acquiring agricultural data. The remote sensing provides various platforms for agricultural survey. Satellite imagery has unique ability to provide the actual synoptic views of large area at a time, which is not possible for conventional survey methods and also the process of data acquisition and analysis are very fast through GIS as compared to the conventional methods. The different features of agriculture are acquired by characteristic, spectral reflectance, spectral signature of agriculture and associated phenomena. In general the research paper emphasizes the utmost need of timeliness and accuracy of the output generated by remote sensing techniques and its calibration with ground-truth and other information systems.

To conclude, history shows that most of the benefits of any new technology go to the early adapters and those who are adopting new tools and are innovative enough to adapt the tools locally. Using geospatial technology as a planning and measuring tool in agriculture and natural resources is expected to follow the same pattern. Today, geospatial technology is no longer a luxury for the academe, scientist, and policy makers, it now becomes a necessity for effective and efficient governance.

REFERENCES

[1] Bantayan, N. C., S. C. Aquino-Ong, and A. M. Palijon. ,1999. Charting landscapes the GIS way. Geo-Asia Pacific. December 1999/January2000 Issue:21-25.

[2] Estes, E. and W. Leslie.,1974. Remote sensing techniques for environmental analysis, Hamilton publishing company, California USA.

[3] Galvez M.,2011. Rice harvest can be predicted. The Philippine Star. Downloaded from the Internet. July 18, 2012. http://www.philstar.com/nation/rticle.aspx?publication SubCategoryId=67&articleId=693055

[4] Godilano, E. C. and J. Bennet.,2004. Capitalizing on new technologies for improving crop water productivity: Space technologies, short and long-term weather forecasting. In Journal of Environment & Development. University of California at San Diego, USA.

[5] Godilano, E. C.,2009. Unified and enterprise geospatial information systems (UEGIS) for philippine agriculture. A project proposal document commissioned by DA Information Technology Center for Agriculture and Fisheries (ITCAF). June 2009.

[6] GIS Talk.,2010. Remote sensing for agriculture project in the philippines. GIS in Education. Downloaded from the Internet. July 15, 2012. http://www.educationgis.com/2010/10/remote-sensing-for-agriculture-project.html

[7] Green and Invins.,1985. Time of sowing and yields of winter wheat. Journal of Agricultural Science. Cambridge, USA.

[8] Francis,A. and A. Nelson.,2012. Snapshots from space. Downloaded from the Internet. July 15, 2012. http://23.23.183.47/index.php?option=com_k2&view=item&id=10610% 3Asnapshots-from-space&lang=en

[9] Jiao, X., Y. Bangjie, and P. Zhiyuan.,2006. Paddy rice area estimation using a stratified sampling method with remote sensing in China. Transaction of the CSAE. 22(5): 105-111.

[10] Lizarondo, M.S.,2010. Food crop forecasting in the Philippines. Downloaded from the Internet. July 18, 2012. http://bas.gov.ph/?ids=techpapers

[11] Major,D.G.,Schaalje,G.B, Asrar G, Kanemasu E.T ,1986. Estimation of whole plant biomass and grain yield from spectral reflectance of cereals. Canadian Journal of Remote Sensing 12(1), pp 47-54

[12] Obico, M.R., E. C. Paringit.,2011. Discriminating and mapping rice ecosystems in Central Luzon Philippines using ENVISAT ASAR Images. MSc Paper. Applied Geodesy and Space Technology. University of the Philippines Diliman, Quezon City 1101, Philippines.

[13] Reyes, T. Jr.,2009. Geographic information systems and remote sensing in the philippines: Historical Proceedings. Downloaded from the Internet. July 20, 2012. http://www.scribd.com/doc/17595697/Reyes-Philippine-GIS-RS-History

[14] Rudoff and Batista,1990. Spectral response of wheat and its relationship to agronomic variable in the tropical region. Remote Sensing of Environment 31, pp 53-63.

[15] Torre, de la, JC. And Ed Alosnos.,2008. GIS-Remote sensing applications. In Philippine Rice R&D Highlights 2008. Philippine Rice Research Institute, Maligaya Science City of Muñoz 3119.

[16] Tucker,C.J., B.N.Holben, J.H.Elgin,J.E.Murtey. ,1980. Relation of spectral to grain yield variation. Photogrammetric Engineering and Remote Sensing 46(5), pp 43-66.

[17] Yun,S., Hao Liu, et.al., 2012. RADARSAT data for operational rice monitoring and its potential for yield estimation. Downloaded from the Internet. July 15,2012. http://www.geospatialworld.net/index.php?option=com_content&view=article&id=14855%3Aradarsat-data-for-operational-rice-monitoring-and-its-potential-for-yield-estimation&catid=114%3Aagriculture-crop-yield&Itemid=41

ACCRONMY AND ABBREVIATION

AFMA	Agricultural and Fisheries Modernization Act
ANR	Agriculture and Natural Resources
APEC	Asia and Pacific Economic Cooperation
BAS	Bureau of Agricultural Statistics
DA	Department of Agriculture
DAR	Department of Agrarian Reform
DENR	Department of Environment and Natural Resources
DILG	Department of Interior and Local Government
DoD	Department of Defense (USA)
ESA	European Space Agency (EU)
ERSGL	Environmental Remote Sensing and Geoinformation Laboratory
FAS	Foreign Agricultural Service (USA)
FSSP	Food Staples Sufficiency Program
GIS	Geographic Information System
GRO	Geospatial Resource Officer
HLURB	Housing and Land Use Regulatory Board
ICT	Information and Communication Technology
IPG	Institute of Photogrammetry and Geodesy
IRRI	International Rice Research Institute
LAI	Leaf Area Index
GOs	Government Organizations
GPS	Global Positioning System
MODIS	Moderate Resolution Imaging Spectroradiometer (USA)
NAMRIA	National Mapping and Resource Information Authority
NASA	National Aeronautic Space Administration (USA)
NGOs	Non Government Organizations
PECAD	Production Estimates Crop Assessment Division (USA)
Philrice	Philippine Rice Research Institute
POC	Provincial Operations Centers
PPO	Policy and Planning Office
PRC	Peoples Republic of China
RADAR	RAdio Detection and Ranging
RFUs	Regional Field Units
RS	Remote Sensing
SAFDZ	Strategic Agricultural Fisheries Development Zone
SAR	Synthetic Aperture Radar
UEGIS	Unified and Enterprise Geospatial Information Systems
UPLB	University of the Philippines at Los Baños
USA	United State of America
USDA	United State Department of Agriculture (USA)
VIs	Vegetative Indices

Application of Remote Sensing and Geographic Information Systems on Crop Productivity in Papua New Guinea：An Information Paper from a Land Use Planning Perspective

Stanley Oa[1], Mika Andrew[2] and Kenneth Nobi[3]

1. Senior Soil Scientist and Acting Chief Land Use Officer, Department of Agriculture & Livestock, PNG;2. Chief Land Use Officer and National Coordinator for the Pacific Adaptation to Climate Change (PACC) Project, PNG;3. Land Resources Information/GIS Officer (Papua New Guinea Resource Information System – PNGRIS)

rjsuat@hotmail.com, kennethnobi@hotmail.com

***Abstract*—Written from the perspective of an agricultural land use planner and practitioner, the paper begins by briefly giving a background on Remote Sensing (RS) and Geographic Information System (GIS) technologies in terms of their inception into the economy and their applications. Much of what is reported is based on the experiences and observations as well as the limited publication that has been documented to date on the use of these technologies in Papua New Guinea (PNG).The introductory parts of this paper point to the time when these technologies were introduced into the economy; following this is a brief on the current status of the knowledge infrastructure and the demand for GIS personnel in the economy. The later parts of the paper focus on the Papua New Guinea Resource Information System (PNGRIS) and what it is used for and where the future of this system can be utilised to its fullest potential in some of the areas we think it should be use for especially in crop productivity forecasting. The final few paragraphs highlight one of the most pressing areas for a developing economy which is capacity building for both universities and industries in the use of these technologies. From a land use planning perspective, the paper makes it clear that the harnessing of PNGRIS with RS technology can allow for the potential exploration of other crop productivity areas such as yield prediction to better aid in the agriculture land use planning process so that decision-makers can be better informed.**

Keywords—Papua New Guinea Resource Information System, physiological crop models, crop productivity analysis, remote sensing, geographical information systems.

INTRODUCTION

This paper has been prepared purposely to inform the workshop participants the status of knowledge and application of Remote Sensing (RS) and Geographic Information System (GIS) technologies used in Papua New Guinea (PNG) to aid in crop productivity analysis. Written from the perspective of an agricultural land use planner and practitioner, the paper begins by briefly giving a background on these technologies in terms of their introduction into the economy, the current status on of knowledge and application, as well as an insight into one of the most comprehensive GIS databases and the future potential uses/applications of this GIS database in PNG. Most of what is reported herein is based on experiences, observations and the limited publication that has been accessed on the use of these technologies in PNG.

KNOWLEDGE AND APPLICATION OF REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEM IN PNG

Since the introduction of RS and GIS technologies into the economy in the early 1980's, 'GIS' was seen to be a novel technology only for the learned to use. Later in the early 1990s RS using satellite data[Technically RS also includes aerial photography given that both capture data from remotely mounted equipments/cameras set on different platform s and heights (i.e. Satellite at very high altitudes compared to aero-planes at much lower altitudes)]began to be used commonly and came to be the partner technology in providing derivative products to form the basis of the development of GIS databases. The Department of Agriculture and Livestock's Land Utilisation Office was amongst one of the first Government agencies to be introduced to these technologies as early as 1980 (Montagu 1995; Beconytė et al 2008). Knowledge on the use and application of these technologies has increased since then with the introduction of these technologies as undergraduate courses at the PNG University of Technology and the University of PNG. A remote sensing unit was established in 2003 at the University of PNG to acquire, process, analyse, and distribute current satellite imagery and data of PNG to academic institutions, government departments, NGOs, private sector and the general public. The demand for well-trained GIS managers and professionals still remains high in PNG especially within the extractive industries and renewable resources sector.

Many of the GIS databases housed by government agencies, NGOs and national institutions in PNG were set up for specific purposes. About 50% of the GIS were established for the purposes of managing terrestrial and marine resources. Within the agriculture sector there are a number of GIS databases and crop and land evaluation models used to assess crop productivity. The most comprehensive GIS database is the Papua New Guinea Resources Information System (PNGRIS) which is amongst one of the best GIS the economy has and it is housed within the Department of Agriculture and Livestock's Land Utilisation Section (DALLUS).

The PNGRIS is a PC-based geo-referenced database which contains natural resource information on climate parameters, soils, landform and socio-economic data on population distribution, rural land use, small-holder economic activity and land use potential data (Bellamy & McAlpine 1995; Trangmar, Giltrap, Burgham & Savage 1995). Other GIS databases and crop evaluation models (see Figure 1) were further developed from PNGRIS such as the Forest Rapid Resource Appraisal (FRRA), Mapping Agricultural Systems Project (MASP), Madang Resource Information System (MADRIS) (Bellamy & McAlpine 1995). In its second upgrade, the focus shifted to problem solving and since smallholder farming activities (which includes subsistence farming was) given priority, the question of how to assess crop productivity had to be carefully framed. Tabulated local crop data had to be compiled to relate the requirements to the data that was already contained in the PNGRIS so that a crop-based evaluation could be applied in determining the suitability of crops for a particular region or site (McAlpine, Keig, Bellamy, Bleeker, Cuddy, Hackett, Hide & Saunders 1986). Two software packages were developed elsewhere (i.e. PlantGro & Automated Land Evaluation System-ALES) and introduced later to be used in doing evaluations for crop suitability. These software packages are modified version of the ALES; the PNGLES is one that is frequently used. The PNGRIS database was recently upgraded in 2007 and contains a more detailed soil mapping, topographical data created using the 'upness index[The upness index is part of the Fuzzy Landscape Analysis Geographic Information System (FLAG) model of Roberts et al 1997, Summerrell et al 2005, adopted by Bryan and Shearman 2008]' from the UPNG DEM[The UPNG DEM is a computerized grid representing the altitude of PNG and each grid measures 90m x 90m in size with each cell containing a measurement of the average height above sea level. The DEM was initially created using the NASA Shuttle Radar Topography Mission (SRTM) data (Bryan and Shearman 2008)]. The scale at which all the datasets (six layers) have been mapped is at 1:250 000 which allows for the project and farm level planning.

The major function of this GIS is used to identify suitable areas for certain types of land uses (mostly agricultural land uses) given certain criteria as well as determining the most suitable types of land use types for specific areas and sites using crop models (see Figure 1).

Remote sensing applications and the derived products are used as components of many of the GIS databases used in PNG. The UPNG Remote Sensing Centre does most of the remote sensing work in PNG and its applications are more into the monitoring of land cover and land use changes across PNG. There is no direct use of remote sensing in determining crop performance or associated uses (e.g. in determining moisture levels) as a means to deducting and making predictions on crop performance (in terms of growth and yield).

FUTURE USES OF RS AND GIS

With increased knowledge and innovation on the applications of RE and GIS, it has been noted that research into the direct use of RS and GS technology in precision agriculture as a means to aid development or simply to increase food production will become essential as governments and decision-makers realise the cost effectiveness of these technologies. For example it has been noted elsewhere (Carbone, Narumalani & King 1996) that RS and GIS technologies can be used with some of the physiological crop models mentioned to determine soil moisture to predict potential yield. The era of using conventional techniques in finding solutions to increase food production and food security issues will someday come to an end as decision-makers opt for cost-effective technologies. This area has not being explored enough but examples of work done elsewhere (Sawasawa 2003) show that RS techniques (based on spectral reflectance - NDVI) is cheaper. The cost of acquiring the images maybe expensive but compared to having to actually carrying out a detail physical verification work, the RS technology can reduce the cost of physically conducting surveys.

With climate change and its impacts on natural ecosystems including peoples livelihoods; the need of RS and GS technologies will become more important to monitor crop development and growth and early yield will become important. In PNG, that is the future direction that we see for RS and GIS technologies. At the present moment the UPNG Remote Sensing Centre contributes less to industry work as it concentrates on research work. Capacity building in terms of the number of RS centres is limited as well as the qualifications of graduates streaming out from universities here in PNG. It is hoped that another remote sensing centre will be set up to serve the industries in the near future especially within the DALLUS to look into the area of using remote sensing technology to explore some of the areas mentioned earlier to aid in making decisions in crop productivity issues.

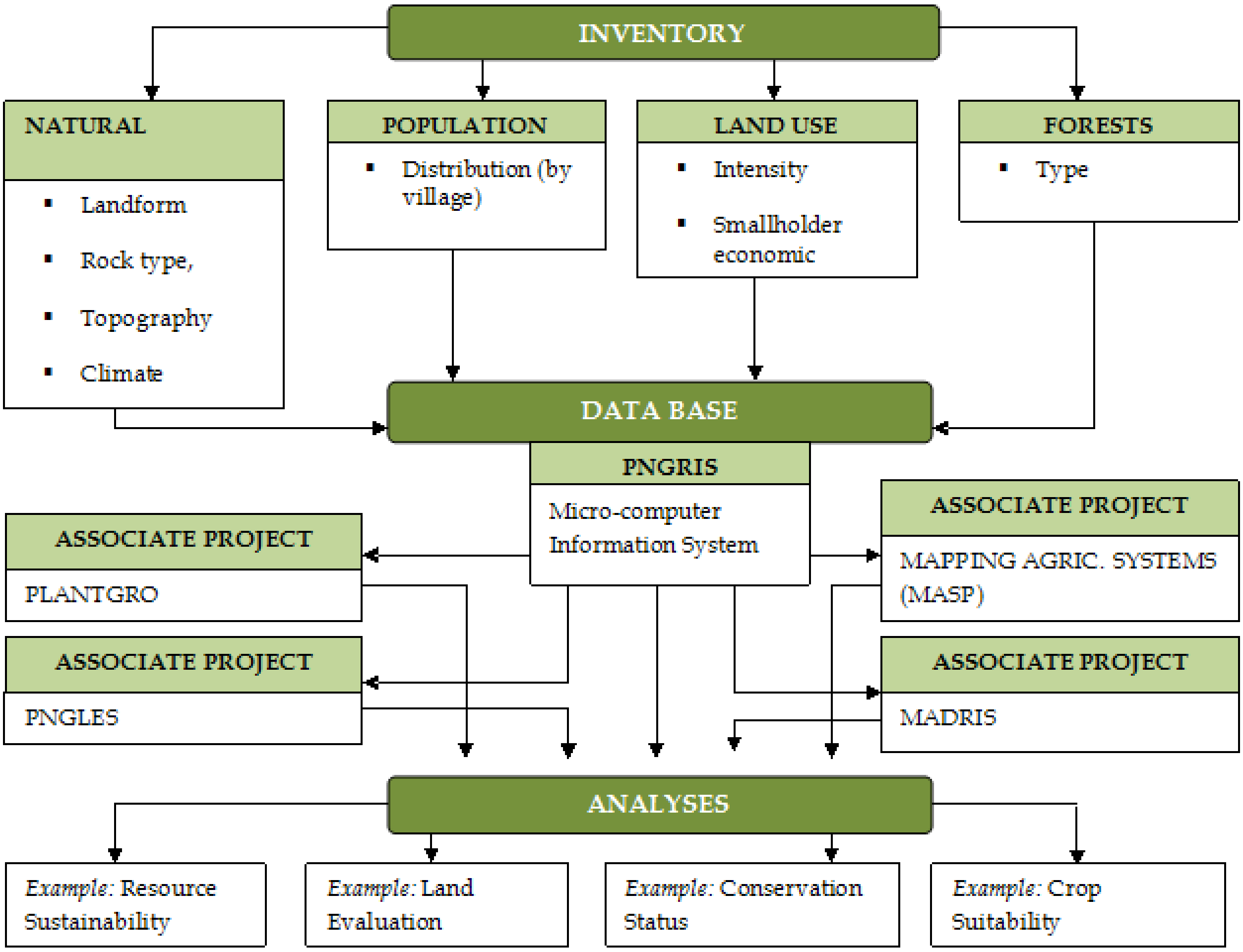


Figure 1. PNGRIS Components (Modified after Bellamy and McAlpine 1995)

CONCLUSION

Purposely to inform the workshop participants the status of knowledge and application of Remote Sensing (RS) and Geographic Information System (GIS) technologies that are being used in Papua New Guinea (PNG) to aid in crop productivity analysis, the paper basically has been prepared based on the experiences, observations and the limited publication available in the economy. It has been written from the perspective of an agricultural land use planner and practitioner and while some general information on the use of these technologies have been stated herein, for the most part the PNGRIS micro-computer based GIS database has been the most GIS discussed here as it forms the one of the core functions undertaken by the DALLUS to determine sites or areas where crops will be able to perform with minimal inputs in to the local production systems.

On the basis of the knowledge and use of these technologies, it is evidently clear that there are many GIS databases hosted in PNG by various government agencies and NGOs but amongst this is the PNGRIS which was developed originally for agriculture land use planning but today the data contained in this database can be used in providing solutions to a range planning uses in various sectors (e.g. conservation, health, engineering etc.) There is however a need to build the capacity to use this system for various applications especially in the direct use of remotely-sensed data for determining other variables for crop growth and production. Some of the future areas that have been highlighted in this paper are in the areas of yield prediction. It is hope that this paper has been informative to participants to up to this time on the status of the knowledge and use of RS and GIS technologies in PNG.

REFERENCES

[1] Beconytė, G., Govorov, M., Ningal, T.F., Paršeliūnas, E. ,Urbanas, S. 2008. Geographic information E-Training initiatives for national spatial data infrastructures. Technological and Economic Development of Economy, 14(1): 11–28

[2] Bellamy, J.A. and McAlpine, J.R. 1995. Papua new guinea inventory of natural resources, population distribution and land use handbook. Second Edition. PNGRIS Publication No.6. Australian Aid Agency for Development. 162 p.

[3] Bryan, J.E. and Shearman, P.L. 2008. Papua new guinea resource information system handbook. Third Edition. PNGRIS Publication No.7. University of Papua New Guinea. 233 p.

[4] Carbone, G.J., Narumalani, S. , King, M. 1996. Application of remote sensing and geographic information system technologies with physiological crop models. PhotogrammetricEngineering & Remote Sensing, 62(2) 71-179.

[5] McAlpine, J.R., Keig, G., Bellamy, J.A., Bleeker, P., Cuddy, S.M., Hackett, C., Hide, R.L. Saunders, J.C. ,Freyne, D.P. 1986. A natural resources information system for village agriculture in PNG. research report 1983-1985. CSIRO Division of Land and Water Resources. Canberra. pp 78-86.

[6] Montagu, A.S. 1995. Institutional arrangements for the future management of the papua new guinea resource information system. PNGRIS Discussion Paper No.1. Commonwealth Scientific and Industrial Research Organisation (CSIRO)Canberra.

[7] Office of National Planning & Implementation 1998. Directory of data systems in papua new guinea. unpublished technical report. 219 p.

[8] Sawasawa, H.L. 2003. Crop yield estimation: integrating RS, GIS, management and land factors. A case study of Birkoor and Kortigiri Mandals-Nizamabad District India. Thesis. International Institute for Geo-Information Science and Earth Observation, Enschede, The Netherlands.

[9] Trangmar, B.B., Giltrap, D.J., Burgham, S.J.,Savage, T.J. 1995. Land suitability assessments for selected crops in papua new guinea. PNGRIS Publication No.8. Australian Aid Agency for Development. 84 p.

Application of Remote Sensing and GIS Technology on Crops Productivity among APEC Economies : Experiences of Chinese Taipei

Horng-yuh Guo
Agricultural Research Institute of COA, Chinese Taipei
hyguo@tari.gov.tw

***Abstract*—RS and GIS technology becomes popular and useful tools for natural resources management around the world for food security and food safety. The agriculture sector of Chinese Taipei Economy has developed and applied RS and GIS technology more than 30 years. This paper reviews two parts of experiences; one is GIS, especially focus on soil information application developed progresses on crops productivity, another part is land cover database derived by remote sensing method and its applications. The relevant achievements contain the soil productivity classification of paddy fields, soil productivity promotion planning, soil management groups, assessment of the susceptibility of nitrogen fertilizer and soil quality monitoring. The farmlands land cover database of Chinese Taipei Economy was based on remote sensing technology. More than 70 species crops including major staple foods, upland crops, vegetables, fruits and bamboo distribution layers were mapped. This information could be inquired the distribution of crop for agricultural management and applied to related natural resources management decision making through internet. Future researches should focus on applying RS, GIS and ICTs (Information community technology) tools with knowledge management (KM) to increase crops productivity on the farm.**

Keywords—Geographic information system, farmlands land cover map, field survey, satellite images analysis and interpretation, aerial photo interpretation

INTRODUCTION

Food security, defined as when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life (World Food Summit, 1996). For most of the history of mankind, food supply was a precarious commodity. Recently, increased intensity and frequency of storms, drought and flooding, altered hydrological cycles and precipitation variance have implications for future food availability.

Increasing population and consumption are placing unprecedented demands on agriculture and natural resources. Today, approximately a billion people are chronically malnourished while our agricultural systems are concurrently degrading land, water, biodiversity and climate on a global scale. To satisfy the growing, worldwide demand for grain, two broad options are available: (1) The area under production can be increased or (2) productivity can be improved on existing farmland (Edgerton, 2009). There are several options for improving crops productivity on existing farmland, GM biotechnology, fertilizers and pesticides applications can be options, but most of consumers around the world seem to have aversion attitude on these kinds of agricultural practices. To meet the world's future food security and sustainability needs, food production must grow substantially (Foley et al, 2011）.

The evolving capability of geographical information systems (GIS) makes it possible for computer system to handle geospatial data in amore efficiency and effective way (Weng, 2010). Remote sensing (RS) systems usually collect data on multiple dates, making it possible to monitoring changes over times of the earth surfaces. RS technology provides cost-effective large-coverage data in a raster data format for analysis and modeling application. The World Bank (2011) suggested that increasing crops, livestock, and fishery productivity through ICTs (Information community technology). The first type of ICTs that improves productivity includes tools that collect agricultural data. GIS and remote sensing (RS) technologies are useful tools that applied in agricultural sectors. New ICTs help to characterize field conditions, and help farmers improve soil and land productivity. Accurate soil analysis and improved farming practices are needed urgently because productivity gains are high in healthy soils and where pesticides, fertilizer, tools, and machinery are used properly (The World Bank, 2011). Correcting past damages and ensuring future yields will require farmer, governments and development partners to mitigate the effects of climate changes and environmental degradation.

SOIL DATA SOURCES

Chinese Taipei economy has implemented several soil survey programs for the past 50 years. Systematic soil surveys of agricultural lands, hill lands and forest lands at a detail scale (1:25,000) were implemented in Chinese Taipei economy in the period 1960-2006. It became to well understand the soil characteristics of Chinese Taipei after a 46 year-period soil survey projects. Some special purpose soil survey programs were conducted during this period, such as: marginal lands land use capability survey (1960) and soil fertility survey of farmlands (1967, 2008), fertility capability classification (1983) for land use planning and fertilizers management. The aims of most of programs were concentrated on soil fertility topics due to lacking fertilizers and food security consideration during that period (Guo et al., 2002).

Soil information system can provide the information of the pattern of the soil cover and its characteristics for us to analyze and display the topics of soil resources management. Soil information system applied in the agriculture sector was tracked back to 1990s. The soil data provided for universities and other sectors and was applied in the fields of environment protection, land management, nature resources management and civil engineering application. More than 30 of applicants from different institutes asked for soil information each year.

There are 15 attributes data of each map unit in this system include: parent material, soil morphology (color or special feature), soil formation, soil drainage class, slope class, soil reaction, soil calcareous properties, soil type, four layers of different depth of soil texture class of the representative profile and soil phases(salinity, stoniness and gravelly) . The attributes of soil units except soil reaction are qualitative, i.e. by grades or classes classification. Chinese Taipei agricultural research institute (TARI) has applied these soil databases of farmlands to recognize the distribution and assess the grade of low-productivity croplands.

EXPERIENCES OF SOIL INFORMATION APPLICATIONS FOR INCREASING CROPS PRODUCTIVITY

Soil information was applied on several fields by TARI, such as: the paddy soil productivity classification(1986), soil productivity promotion planning (1993) , soil management grouping (1998) , assessment of the susceptibility of nitrogen fertilizer (2000) , and soil quality monitoring (2001) . It also is a major resource of farm fertility management guidance for farmers through display soil fertility on maps and internet.

THE PADDY SOIL PRODUCTIVITY CLASSIFICATION

The major staple food of Chinese Taipei economy is rice. Rice production and sustainability is the most important task of agriculture sector of Chinese Taipei economy.

The paddy soil productivity classification project aims were: 1) to simplify the soil map and show that the limiting factor of the potential production of paddy productivity, 2) to provide the information for paddy field utilization and improvement of production technology, 3) to provide the information for the basis of land use and planning.

The project was based on land capability classification concept, defined that is a system of grouping climate and soils primarily on the basis of their capability to produce rice. The climate and soils are grouped according to their limitations for rice, the risk of damage if they are used for rice, and the way they respond to management.

Paddy soil productivity classes and in most cases, subclasses are assigned to each soil. They suggest the suitability of the site for rice and provide a general indication of the need for conservation treatment and management. There are 10 productivity classes in this system. Capability classes are designated by Roman numerals (I through X), which represent progressively greater limitations and narrower choices for practical rice production. The capability was responded to the yields of rice per unit of land in those years so that the information application can be closed to the farmer. The yields per land unit maybe change due to management and new breeding improved, but the classes still responses the relative rice productivity.

In the system, the agro-climatic condition was classified into 6 classes according to the potential of combination of climate factors such as: temperature, solar radiation, rainfall, wind, cold hazard that affect on the production of rice. The agro-climatic data was collected from weather bureau and analyzed, classified and mapped. The rice yield per land unit was responded to the weighting of agro-climatic factors and rating of classes.

The paddy soils are grouped into 4 classes and 11 subclasses according to the potential of each soil for the production of rice. The rice yield per land unit was also responded to the weighting of soil factors and rating of classes, but the weighting of soil factors effects were less than that of agro-climatic factors. The paddy rice classes' boundaries were based on that of soil mapping units.

The paddy soil productivity classification maps are used as the target yields reference of site specific nutrients management to guiding fertilizer amount and regional land use planning, it also applies on land administration regulation to keep good farmlands.

SOIL PRODUCTIVITY PROMOTION PLANNING

Common biophysical factors that contribute to yield losses in farmers' fields are as the followings: nutrient deficiencies and imbalances (nitrogen, phosphorus, potassium, zinc, and other essential nutrients), water stress, flooding, soil problems (salinity, alkalinity, acidity, iron, aluminum, or boron toxicities, compaction, and others), weed pressures, insect damage, diseases (head, stem, foliar, root), lodging (from wind, rain, snow, or hail), suboptimal planting (timing or density), inferior seed quality.(Lobell et al, 2009, FAO, 1976 ） defined some land qualities related to soil productivity from crops or other plant growth, such as: moisture availability, nutrient availability, oxygen availability in the root zone, adequacy of foothold for roots （shallowness）, conditions for germination, workability of the land (ease of cultivation), salinity or alkalinity and soil toxicity.

By the concept of FAO land qualities, the low-productivity soils assessment chose several land qualities that criteria could link with the soil information system of Chinese Taipei Economy farmland, such as: shallowness, stoniness, workability, salinity, acidity, water logging, droughty（moisture availability）, nutrients deficiency. The low-productivity soils criteria inferred from the soil survey reports, research reports, and derived soil quality and fields experience. The soil database was evoked in relation with criteria to assess and map the distribution of the low-productivity soils. Criteria and the assessment results were shown on Table 1.

Table 1. The soil attributes of soil information applied on the assessment of low productivity soils in Chinese Taipei Economy.

Low-productivity soils	Attributes used for assessment	Acreages (ha)
Shallowness	Soil types; profile depth; soil phase	137,610
Stoniness	Soil phase	28,390
Tillage practice and soil workability	Soil type; profile texture; drainage class	107,010
Salinity	Soil salinity; drainage class	62,970
Acidity	Soil formation & pH	190,830
Water logging	Soil type; drainage class	47,480
Droughty	Profile texture; drainage class	55,970
Nutrients deficiency	Parent materials; pH; calcareous materials	268,980

Shallowness, the shallowness soil defines that the depth is less than 25 cm has a severe limitation and the depth between 25 cm to 50 cm has a moderate limitation. Sixteen percentages of farmlands in Chinese Taipei economy, 137610 hectares, with shallowness limitation cover on alluvial fan apical regions, mountain outwashes, riverbeds and hill lands. Stoniness, stoniness means stones in the surface soil affect crops production and cultivation. Stones in the soil may reduce the soil functions those provide crops growth, such as: nutrients supply, water holding capacity and root crops quality. Stony soils damage agricultural machines and harvest machines, too. It has nutrient supply, water supply, crop selection and workability limitations for crops production. Stony soils reclamation is very difficult, because it is scarce of soil resource for reclamation. The stony soil can be good productivity orchards, if the fields have an irrigation system with properly fertilizer management. Tillage practice and soil workability, the term tillage practice and soil workability refer to the mechanical plow availability of the surface soil and seedbed preparation. A clay soil is more likely to be difficult to work, sticky and plastic when wet and prone to drainage problems, but hard when dry （Gardner et al,1999）. The clayey soil is of very hard consistence when dry and very plastic and sticky when wet. Therefore the workability of the soil is often limited to very short periods of optimal water status. Generally, the soil texture is heavier than silty clay, has tillage practice and soil workability problems. It estimated that 107,010 ha of farmlands have tillage practice and soil workability problems in Chinese Taipei economy. Soil salinity, saline soils are soils in which a high salt content dominates the problems related to agricultural land use. They are characterized by an electrical conductivity (EC) of typically more than 4 dS/m. Saline soils occur in the southwestern coast plains, former inlands sea and depressed areas due to lands sink, under a hot climate with a distinct dry season. Soil acidity, acid soils are characterized by a pH that is strongly acid (4.5-5.5) to extremely acid (<4.5), a low cation exchange capacity and a low base saturation. It estimated that 190,830 ha of farmlands have soil acidity problems. Many good results of the strongly acid soil reclamations have conducted in Chinese Taipei, including: liming the acid soils for upland crops, application of phosphate fertilizer to newly submerged latosols used for rice production and fertility improvement of latosolic paddy soils （Wang,1984）. The paddy field in strongly acid soils was recommended apply rice husk （10T/ha）or silicates slag （3T/ha）every three years for several years. Water logging, water logging is the condition of the soil that is saturated with water and lacking most or all of the soil air. In this study, poor and very poor soil drainage classes and imperfect soil drainage with one of silty clay texture in the profile are classified water logging. It estimates that 47,480 ha of fields have water-logging problems in Chinese Taipei economy. A large area of poorly drained paddy fields has been ameliorated by improvements in the regional drainage system for a long time. Rice yields increased significantly for the second crop in the rainy season (Wang, 1984) . Surface ditches and increasing the cropping bed level to improve water logging problem for wax apples production in Pingtung area has conducted this year. Soil droughty, soil water is essential to soil organisms and plant life. A decline in soil water content results in a reduction of plant growth and root system development. Stony/gravelly soils, shallow soils and sandy soils have low water holding capacity. The agricultural potential of sandy soils depends on the availability of sufficient water for crop cultivation and the provision of nutrients. Nutrients deficiency, soils diagnostics and plant tissues analysis service has preceded for several years, more than fifteen thousands of farmers per year have their benefits of fertilizers application recommendation from this program. However, the soils and plant tissues analysis service program cannot be satisfied for all farmers due to the laboratories capacities. Soil information can be applied to indicate some nutrients deficiencies such as: zinc, iron, manganese boron deficiencies are easily found in the calcareous soils, because these nutrients availability is low in alkaline soils (pH >7.8) . It estimates that 268,980 ha farmlands have nutrients deficiency problems. Detail nutrient problems in Chinese Taipei economy will be discussed in the following section.

Soil information system provides a clear understanding of low productivity soils and degradation soils in Chinese Taipei economy farmlands. It can be: 1) to provide an overview of the relative extent of physical resources limitations to agriculture and other forms of land use in the whole economy, 2) to highlights area which call for the treatment or management of specific land resources constraints, so the regional or national action plans can be better focused on specific problems, 3) to indicate the limitations of the data and the amelioration methods, and hence the priority needs for improved information and researches. The information was provided for decision making of soil amelioration and regional soil management planning. The shortage of this system is the qualitative attributes data and lacking of nutrients states information for the intensified farming system.

SOIL MANAGEMENT GROUPS

Soil series category is the most homogeneous category in the taxonomy used around the world, but the soils of a series have a relatively narrow range in set of properties (USDA,1962) . Soil maps provide soil properties information for the applicants. However, soil classification is focus on soil features of soil morphology and soil genesis. The complexity of soil classification category may be not suitable for field management. Soil management grouping is a work to group several similar soil series into one soil management unit by GIS method. The categories of a soil management unit were parent materials, soil formation process, drainage class, profile texture. Chinese Taipei economy has 643 soil series in the farmland area, comparing with soil management group has103 units and only 63 units cover the major farmland area. Each township may be less than 5 soil management unit categories. It makes the farming technologies transfer to farmers become easier than before. The farmer also has clear recommendation, simplify of soil information for field practice.

SOIL FERTILITY DATABASE

The basic soil attributes data that soil survey reports provided could not be satisfied with the requirement of intensified farming system operation and rapid-changing soil quality (EPA, 2006). TARI has conducted a soil fertility survey program, designed as a grid system sampling with a cell resolution of 250m*250m, since 1992 and provided the detail soil management information for the requirement of farmers. The system application focuses on the soil fertility and plant nutrition management of farmland. The attribute data include: pH, Mehlich's No. 3 extractable nutrients, exchangeable bases, CEC, OM, 0.1M HCl extractable heavy metals and exchangeable Al. These attributes are quantitative data. It is very easy to calculate soil exchangeable bases percentage and lime requirement for different crops. The map indicates the soil fertility properties such as the major and micro nutrients contents of land of the farmer. It recommends the soil management and fertilizer application for decision-maker and farmer to achieve the goals of applying fertilizer appropriately, reducing the agricultural chemicals input, improving the crop quality, food safety and environment protection. The data can be used for monitoring soil quality, too. These attribute data will be as compensation for the soil survey data shortage of the management of soil nutrients and food safety protection.

SOIL QUALITIES CHANGES MONITORING

The soil quality of the farmlands in Chinese Taipei economy is somewhat on degradation; the new soil data show some evidences as following: (a) Soils acidification: pH decreases 0.5 units on the surface soils on average (compared with 1967 data). (b) Phosphorus accumulation: 80% farmlands have no response with phosphorus fertilizer because of phosphorus accumulation on the surface soils. (c) Nutrients unbalance: 60% farmlands have unsuitable soil nutrients condition, such as: pH, microelements deficiency and K, Ca, Mg deficiency with high N and P. (d) Soil Pollution: 10.7% farmlands are suspected of pollutant intrusion and 0.56% farmlands should be remedied. A quantity of Zn and Cu is put into the farmlands by applying manures. (e) The data also show SOM increase 0.3-0.5% in most of paddy fields, but it still don't meet the ideal status.

The soil properties and soil fertility in Chinese Taipei economy are not in good quality, however, many crops have good yields; Intensive of fertilizer application and soil management are the reasons of the results. Though improved management and ameliorative measures have been intensively studied to solve these low productivity soils, however, the problems of economical feasibility and social requirement prohibit the program of soil reclamation proceeding.

SOIL INFORMATION APPLICATION ON FOOD SAFETY

New insight in the relationship between soil quality and the quality of food should be used by soil environmental scientists around the world to improve scientific methods to provide tools to estimate risks, set soil standards and reduce the uptake of heavy metals by rice. To assess the risk of the metals in these soils, soil quality guidelines standards have been developed in many countries including Chinese Taipei economy (EPA, 2006).

Many examples stress the need to predict or measure the actual chemical availability of heavy metals in soils in order to estimate the risk related to uptake by crops or the functioning of the soil ecosystem. Despite this knowledge, soil quality standards are usually based on the total metal content and information on the total reactive fraction or the actual availability in soil is scarce. Due to differences in soil composition and origin of pollutants in soil, the degree of availability is different which has resulted in a wide range of soil quality standards.

In 2005, 8 sites of heavy metals-polluted farmlands located at Central part of Chinese Taipei economy were selected for cultivation of 12 cultivars, including japonica type, indica type and sticky rice in a project. Most of farmlands in the research area contain high concentration of cadmium, chromium, copper, nickel and zinc. It was found that the rice varieties have different cadmium uptake rate : the cadmium uptake amount of indica varieties is higher than that of japonica varieties. (Guo et al., 2007) . The influence of soil pH on heavy metal availability is related to its effect on the reactions controlling heavy metal concentrations in the soil solution. Under acid conditions, sorption of heavy metal cations by soil colloids is at a minimum, and the solution concentrations are relatively high (McLaren, 2003). As soil pH rises, sorption of heavy metal cations increases and the solubility of oxides decreases. The sorption of heavy metals that occur in anionic forms decreases with increasing soil pH, and hence solution concentrations and availability increase. Usually soil data like organic matter, clay and pH are also available. These data can also be used to predict the uptake of metals by rice because there is a close relation between soil properties and the metal content in the soil and the concentration in the soil solution (Römkens et al., 2004). Finally equation can be predicted the uptake by rice directly from soil properties (de Vries et al., 2008).

$$\text{Log(Metal-rice)} = \alpha_2 + \beta_2 * \log\text{(Metal-soil)} + \gamma_2 * \log(\text{OM}) + \delta_2 * \log(\text{clay}) + \varepsilon_2 * \text{pH}$$

According to this concept, the regression equations to predict cadmium uptake by brown rice from soil properties according to equation are calculated. The results indicate that the prediction of brown rice of cadmium concentration by considering soil pH, OM, CEC. Some experimentally derived models were used to calculate so-called risk map for rice cropping. This was done by calculating the critical levels of cadmium in the soil above which the rice cadmium content exceeds the food quality standard. The soil database from Chinese Taipei economy was used to compare this critical level with actual measured values across the economy. The result indicates that areas exist where the quality of indica species will be not meet the regulation (i.e. cadmium in the rice will exceed the standard of 0.2 or 0.4 mg kg-1). One of the options that are rather easy to implement by farmers is to grow japonica genotype rice in these regions.

LAND COVER DATABASE

Most of land cover data sets were classified into level II in globally, thereby excluding information that is critical for answering key questions ranging from biodiversity conservation to food security to biogeochemical cycling. Information about agricultural land use practices like crop selection, yield, and fertilizer use is even more limited (Monfrenda et al, 2008) . Chinese Taipei economy has produced 3 times of land cover maps during the past 60 years. The information revised and updated period was too long to satisfy the necessary management requirement. A new land cover database project began in 2008. It is expected that the whole economy-wide farming area database could be completed in 2015. The database will be updated 3 times a year to response the management requirement in the future.

Land cover refers to the type of material present on the landscape, such as: water, crops, forest, wet land(Jensen,2005). The land cover database providing the major crops distribution information is to apply on many disciplines, such as: (1).data providing, such as: agricultural statistics, food security early alert system …etc; (2). Lands resources and sites allocation, such as: national land use planning and policies making; (3).natural resources management, such as: irrigation schedule and rural industry planning; (4).crop production management, such as: pest management and fertilizer distribution; (5) natural hazards assessment in agriculture; (6).agricultural economy and marketing; and (7).environment protection, such as: greenhouse gas emission, agricultural non-point source pollution (e.g. fertilizer or pesticide) and the impact of the agricultural pollution on the groundwater quality…etc.

The acreage of each farmland parcel of Chinese Taipei economy on average is about 0.1 to 0.2 hectares and it is cultivated with diversified crops. We select multispectral satellite images with 6 to 10 m ground resolution, which help us extract the information of farmland in a wide area in the shortest time as soon as possible. Multi-temporal images are analyzed, and the phonology cycles of crops information are extracted. High resolution satellite images, aerial photos, farmland parcel map, and ground truth data were collected regularly each year. Ground truth is required for satellite images supervised classification. The ground truth map is printed in scale of 1:5,000. It combined the farmland parcel layer with orthophoto map. Some part of ground truth data are used to evaluate the accuracy of images classification.

Knowledge about variations in vegetation species and community distribution patterns, alteration in vegetation phonological cycles, and modifications in the crops phenology and morphology provide valuable insight into the climatic, edaphic, geologic, and physiographic characteristic in an area (Weiers et al.,2004; Jackson and Jensen, 2005). Time is very important when attempting to identify different vegetation types or to extract useful vegetation biophysical information from remote sensing data. In general, the multi-temporal satellite images were applied to classify some crops in the fields. The final classification layer of the satellite image processed by GIS and filled in the farmland parcel map or cadastral map. Finally, a thematic map of crop classification was completed for mass browsing, inquiry, statistic and other application.

Most of orchards and tea gardens are distributed in the hill lands and mountains. Some geomorphologic effect affects the image processing of satellite images. The aerial photo interpretation was used and established the farm land cover map in the hill land region. More than 60 species of fruit trees and other crops stereo pair of aerial photo were collected and compiled a training material for aerial photos interpretation training. The first step of interpretation is to produce a point data layer. After that, a GIS program manipulates the aerial photos into segmentation and interpretation data layer join into the segmentation layer to produce a new map. Airborne and satellite SAR images have begun to be studied for farmland land cover analysis in Chinese Taipei economy to overcome clouds shadows.

TARI has developed an online browsing and query system (Fig. 1) for the public to surf the land cover data in the webpage. The system is based on Web Map Service (WMS) technology. Web GIS Server software was used. The user can apply GIS software to connect the web address of TARI directly and read the map data of WMS format. It is convenience for the public to use land cover data and add value on map data.

More than 70 species of staple food, vegetables and fruit crops grow in the farmlands and the hill lands of Chinese Taipei economy were mapped. These thematic maps were provided information such as: showing spatial-temporal distribution of crops to check the quality of agricultural annual statistics report, evaluating crops damage in productive area, early warning productive acreage for sensitive crops, pest controlling system design, monitoring tea gardens developed in the steep slope area of high elevation mountains, the soil characteristics of major grapes productive area for the decision makers and researchers.

CONCLUSION

This report shows many cases of successful application of GIS and remote sensing technologies on the topics of food production and food safety management in Chinese Taipei economy. A new soil survey program is progressing from 2008 to 2020. The soil survey methods were improved, such as: fields' soil parameters collection, soil data structure and soil data interpretation should follow the new stream of pedology of the world. Agricultural clouds computing system is in design, too. The system including climate data, soil data, and soil analysis data, cadastral data and crop management of knowledge base provides a recommendation of cultivation process for each farmer.

Agriculture is facing new and severe challenges in its own right. With rising food prices that have pushed over 40 million people into poverty since 2010, more effective interventions are essential in agriculture (World Bank 2011). The growing global population has heightened the demand for food and placed pressure on already-fragile resources. It also will require substantial investments in research and extension to support scientific advances and timely development and adoption of GIS and remote sensing technologies that help to close the exploitable yield gap, increase crop yield potential and improve soil quality.

REFERENCES

[1]De Vries W., Römkens P.F.A.M., Bonten L.T.C., 2008. Spatially explicit integrated risk assessment of present soil concentrations of Cd, Pb, Cu and Zn in the Netherlands. Water Air Soil Pollut. 191:199-215.

[2]Edgerton, M.D., 2009. Increasing crop productivity to meet global needs for feed, food, and fuel. Plant Physiology, 149(1):7-13.

[3]Foley, J.A., N. Ramankutty, K.A. Brauman, E.S.,Cassidy, J.S. Gerber, M. Johnston, N.D. Mueller, C. O'Connell, D.K. Ray, P.C. West, C. Balzer, E.M. Bennett, S.R. Carpenter, J. Hill, C. Monfreda, S. Polasky, J. Rockström, J. Sheehan, S. Siebert, D. Tilman, D.P.M. Zaks, 2011. Solutions for a cultivated planet. Nature, 478: 337–342.

[4]EPA, 2006. Soil and ground water protection. Available at: www.epa.gov.tw.

[5]FAO. 1976. A framework for land evaluation. Soil bulletin No.32. 72 pp. FAO, Rome, Italy.

[6]Gardner, G.M.K., K.B. Laryea , P.W. Unger. 1999. Soil management through tillage/no-tillage, pp.65-78. In: Soil physical constraints to plant growth and crop production. AGL/MISC/24/99, FAO, Rome, Italy.

[7]Guo, H.Y., T.S. Liu, C.L. Chu, C.F. Chiang , M.J. Yeh 2002 Soil information of Chinese Taipei and its development. p.1-38, proceeding of "Conference of soil information application", Taipei.（In Chinese）

[8]Guo, H.Y., T.S., Liu, C.L. Chu, C.F. Chiang,P.F., Römkens 2007 Prediction of heavy metal uptake by different rice species in paddy soils near contaminated sites of Chinese Taipei. Proceeding of " The 8th Conference of East and Southeast Asian Federation of Soil Science Societies (ESAFS）", Tsukuba, Japan.

[9]Jackson, M.W. ,J.R. Jessen, 2005. An evaluation of remote sensing-derived landscape ecology metrics for reservoir shoreline environmental monitoring, Photogrammetric Engineering & Remote Sensing, 71(12):1387-1397.

[10]Jensen, J. R. 2005. Introductory digital image processing: A remote sensing perspective, 3rd ed., Pearson Education, Inc.

[11]Lobell, D.B., K.G.. Cassman, C.B. Field, 2009. Crop Yield Gaps: Their Importance, Magnitudes, and Causes. Annu. Rev. Environ. Resour.. 34:179–204.

[12]McLaren, R.G. 2003. Micronutrients and toxic elements., in 'Handbook of Processes and Modeling in the Soil-Plant System", eds. D.K. Benbi, and R. Nieder. Food Products Press and The Haworth Reference Press, pp.589-625.

[13]Monfrenda, C., N. Ramankutty, J.A. Foley, 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, Global Biogeochemical Cycles, 22, GB1022, 19 PP., 2008.

[14]Römkens, P.F.A.M., J.E. Groenenberg, J. Bril, W. de Vries. 2004. Derivation of partition equations to calculate heavy metal speciation and solubility in soils. ALTERRA report no. 305. Alterra, Wageningen University and Research Center, the Netherlands.

[15]USDA,1962 Soil survey manual(revised), USDA handbook 210, Washington, D.C.

[16]Wang, S.T. 1984. Management of problem soils in Chinese Taipei, R.O.C. In: Ecology and management of problem soils in Asia, FFTC book series No.27, pp.74-88, FFTC, Taipei, Chinese Taipei, ROC.

[17]Weiers, S.,Bock, M., Wissen, M. ,G. Rossner, 2004. Mapping and indicator approaches for assessment of habitats at different scales using remote sensing and GIS methods. Landscape and Urban Planning, 67:43-65.

[18]Weng, Q., 2010. Remote Sensing and GIS Integration: Theories, methods, and Applications. McGraw Hill Company, Inc. 397p.

[19]World Bank 2011. Food Price Watch. February 2011, http:// INTPREMNET/

[20]Resources/Food_Price_Watch_Feb_2011_Final_Version .pdf.

[21]World Bank, 2011. ITC in agriculture. Resources book. Report No.64605.406pp.

Mapping the Rice Cropping Systems Using Time Series Satellite Data

Chi-Farn Chen

Center for Space and Remote Sensing Research, Central University, Jhongli, Chinese Taipei

cfchen@csrsr.ncu.edu.tw

***Abstract*—Rice is an important economic crop for half of the world's population. Estimating rice-growing areas for production prediction is thus necessary to ensure food security. This study investigated the applicability of time-series satellite data for rice crop mapping. Two case studies of rice crop mapping using time-series SPOT and MODIS data were presented. The first case study was to develop a classification approach for mapping double-cropped rice fields in Chinese Taipei using time-series SPOT NDVI data. Data processing steps included: (1) constructing time-series SPOT NDVI data, (2) filtering the time-series NDVI data using the empirical mode decomposition (EMD) method, (3) classifying double-cropped rice fields using statistical methods (i.e., correlation analysis and sign-test statistics), and (4) assessing classification results. The comparisons between the classification maps and the ground reference maps indicated satisfactory results. The overall accuracy and Kappa coefficient were generally greater than 85% and 0.7, respectively. The second case study utilized time-series MODIS NDVI data to classify rice cropping systems in the Vietnamese Mekong Delta. The time-series NDVI data were also filtered using the EMD. However, rice cropping systems were classified using the linear mixture model (LMM). The classification results verified with the ground reference data indicated the overall accuracy and Kappa coefficient of 71.6% and 0.6, respectively. The area estimates also reaffirmed the strong correlation (R2>0.9) with the government rice area statistics.**

Keywords—empirical mode decomposition (EMD);rice cropping systems;time-series SPOT and MODIS data;Chinese Taipei;Mekong Delta.

1. INTRODUCTION

Rice is an important food crop for half of the world's population (FAO., 2002), occupying approximately 11% of the global cropland area (Maclean, 2002). It plays a vital role in the economy of many developing countries, especially in Asia that accounts for roughly 90% of global rice consumption. The ever-increasing world's population and climate change have triggered compound issues of food security and environmental degradation (Young and Steffen, 2009). To balance the today's food needs while still safeguarding the environment, it thus calls for a jurisdictional rice crop monitoring program on different scales. In this study, efforts were made to develop approaches for rice crop mapping in Chinese Taipei and the Vietnamese Mekong Delta.

Chinese Taipei is a relatively small island, but densely populated. Rice agriculture plays an important role in this island because it provides employment and income for rural populations (Huang et al., 2002b). Rice cultivation in Chinese Taipei is examined yearly because of the food security (Chou et al., 2006). Vietnam is currently the world's second largest rice exporter with more than 80% of grain rice produced in the Mekong Delta. Owing to pressures of rapid population growth and economic development, intensive rice cultivation have caused land degradation in many parts of the region, consequently influencing rice yields (Khoa, 2003). Investigating rice planting areas in Chinese Taipei was implemented through costly interpretation of aerial photos whereas in the Vietnamese Mekong Delta was through costly field surveys. Therefore, an effective monitoring program for rice cultivation areas using remote sensing technology is necessary.

Remote sensing has been long recognised as an indispensable tool for crop monitoring on various scales. For example, MODIS data have widely been used for crop monitoring due to its wide coverage, highly temporal repeatability (Bridhikitti and Overcamp, 2012; Xiao et al., 2006). However, the use of MODIS data for rice crop monitoring in Chinese Taipei is infeasible because the size of rice fields here is fragmental and relatively small (1.1 ha on average) (Huang et al., 2002a). In this study, the time-series SPOT data were thus used to investigate rice cropping systems in Chinese Taipei. Because the optical satellite data were often obscured by various image artefacts, such as clouds that can potentially affect the mapping results, the empirical mode decomposition (EMD) method (Huang et al., 1998) was used in this research to filter out the noise from the time-series data. The algorithm is adaptively decomposes the signal into a number of intrinsic mode functions (IMFs) and a residue (Huang, 1998). From IMFs and the residue, a low-pass filter can be designed to smooth the time-series data.

A number of soft and hard classification methods have been developed for classification of satellite data. The maximum likelihood method is the most commonly-applied classification technique due to its well-developed theoretical base and its successful application with different satellite data types (Bolstad and Lillesand, 1991). However, its performance is only good if the satellite data are parametric. In this study, a classification method based on statistical analyses of the filtered time-series SPOT data was developed to classify the double-cropped rice in Chinese Taipei. To certain degree of very minor inaccuracies in the NDVI values, the linear mixture model (LMM) (Adams et al., 1986) was used to quantify the rice cropping patterns in the Vietnamese Mekong Delta.

The main objective of this study was to investigate the feasibility of using time-series satellite data (SPOT and MODIS data) to discriminate rice cropping systems in Chinese Taipei and the Vietnamese Mekong Delta.

2. A CASE STUDY OF DOUBLE-CROPPED RICE MAPPING FROM SPOT DATA IN CHINESE TAIPEI

2.1 Study sites

Rice is mainly cultivated in three regions of Chinese Taipei, the southeast, southwest, and northern areas, and it is dependent on irrigation availability. Thus, three study sites representative of three main rice growing regions (Taitung, Chiayi, and Taoyuan counties) were selected (Fig. 1). The double-cropped irrigated rice using short-term varieties of rice (approximately 110 days) is commonly practiced. This cropping system consists of two rice crops per year: the first crop (Jan−Apr) and the second crop (May−Sep) (Huang et al., 2002b).

2.2 Data

The SPOT-2, -4, and -5 data for 2005 were used. There were a total of 75 images acquired for the Taitung site, 69 images for the Chiayi site, and 70 for the Taoyuan site. The SPOT-5 data (10-m resolution) were resampled to the same resolution as SPOT-2, 4 data (20-m resolution). The NDVI were calculated for each scene and then stacked into year-long NDVI scenes for each study site. Rice crop maps of such three study sites in 2005 (scale: 1/5,000) were also collected, and used as ground reference data for accuracy assessments (Fig. 2).

2.3 Methods

2.3.1 Data filtering

The time-series SPOT NDVI data obscured by noise were filtered using the EMD (Huang, 1998). Details about the EMD can be found in the text of Hilbert-Huang transform (Huang and Shen, 2005). Based on the initial results achieved from the EMD analysis of the time-series data, it was found that by adding the last two IMFs and the residue, it was possible to separate the noise from the time-series data whilst preserving the amplitude of the NDVI values. Thus, a low-pass filter was designed in this manner to smooth the time-series data.

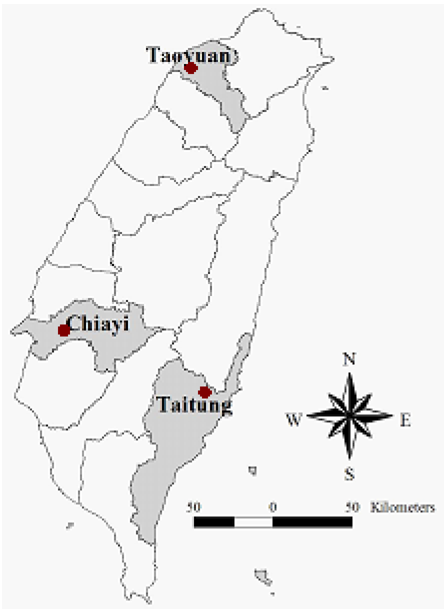


Fig. 1. Location of the study sites relative to the geography of Chinese Taipei.

3.3.1 Training data selection

The training patterns were obtained from the filtered NDVI data for classification. We randomly extracted 100 random rice pixels from the filtered NDVI data based on the ground reference data. The mean pattern for these sampling pixels was then calculated. The correlation coefficients between the mean patterns with 100 sampling pixels were calculated. A histogram of correlation coefficients was then plotted. A threshold was set to identify 95% of the extracted training pixels. The thresholds for the three study sites (Taitung, Chiayi, and Taoyuan) were 0.88, 0.85, and 0.79, respectively.

2.3.2 Classification

For every pixel of the filtered time-series NDVI data, the correlation and sign-test methods were applied to test whether that pixel corresponded to a double-cropped rice pattern. A pixel that was identified as the double-cropped rice pattern must satisfy two conditions: its pattern must be strongly correlated with the mean pattern, and the pattern must also have a median similar to that of the mean pattern. The sign-test statistic was used to test the similarity of two double-cropped rice patterns. In this case, S+ and S- were the number of positive and negative differences, respectively. The test statistic S was chosen such that S was the minimum of the two S+ and S- values. The expressions for the p-value based on exact binomial probabilities, where n is the sample size, are presented as follows.

2.3.3 Accuracy assessment

Pixel-by-pixel comparisons between the classification results and the ground reference maps were performed using the error matrix.

2.4. Classification results

The classification results for the three study sites (Taitung, Chiayi and Taoyuan) were presented in Fig. 2 and Table 1.

Rice fields within the Taitung study site were concentrated along rivers (Fig. 2a). The rice fields in this county were relatively homogenous. Thus, the results of pixel-by-pixel comparisons between the classified maps and the ground reference map indicated the overall accuracy and Kappa coefficient of 93.7% and 0.83, respectively. The double-cropped rice was distributed throughout the Chiayi study area (Fig. 2b). This county was characterized by a dense and well-developed road network. Rice fields in this site were relatively small, and many fields were located along small roads such that problems with mixed pixels were evident. The comparison between the classification maps and the ground reference map showed the overall classification accuracy (85.8%) and Kappa coefficient (0.70). The distribution of rice fields within the Taoyuan study site were scattered throughout the region (Fig. 2c). When comparing the classified maps with ground reference map, the results revealed the overall accuracy and Kappa coefficient of 90.8% and 0.74, respectively.

3. A CASE STUDY OF RICE CROP MAPPING FROM MODIS DATA IN THE VIETNAMESE MEKONG DELTA

$$p = 2\times\sum_{k=0}^{s}\binom{n}{k}\left(\frac{1}{2}\right)^{n} \qquad (2)$$

3.1 Study area

The Mekong Delta lying between 8.5−11 N and 104.5−106.64 E covers 40,000 km2 (Fig. 3). Majority of land in the region was allocated for agriculture in which rice is the dominant crop. There are two seasons with an annual average rainfall of 1,442 mm. The wet season (May−Nov) contributes 80% of the total rainfall. There were five crop seasons in a year: rainy season (Jul−Aug to Dec−Jan), winter-spring (Nov−Dec to Feb−Mar), spring-summer (Mar−Apr to May−Jun), summer-autumn (Apr−May to Jul−Aug), and autumn-winter (Jul−Sept to Oct−Dec). Four rice cropping systems were observed: single−cropped rain-fed rice, double−cropped irrigated rice, double−cropped rain-fed rice, triple−cropped irrigated rice. Single rain-fed rice cropping uses long-term varieties (160−180 days), whereas irrigated-rice cropping systems use short-term varieties (90−100 days).

3.2 Data

The MOD09Q1 MODIS/Terra data (250-m resolution) for 2002 and 2007 were used. The NDVI was used to study the temporal response of rice fields. Other data including: (1) the rice crop map in 2002 (Fig. 4a) (scale: 1/125,000) (Sub-NIAPP, 2002). This map was converted to a raster form and used for accuracy assessment; and (2) rice area statistics for 2002 and 2007 at the provincial level (GSO, 2007) were also collected and used to analyze the relationship between the MODIS-derived rice area and the government rice area statistics. Because this study focused on investigating rice growing areas, non-cropped areas were masked out.

3.3 Methods

3.3.1 Linear mixture model

The LMM used to quantify rice cropping patterns in the study area from the filtered time-series MODIS NDVI data (derived from the EMD method as mentioned in Section 2.3.1) can be expressed as follows:

$$r = M\alpha + e, (1)$$

where r is a vector which represents the temporal NDVI value for a column pixel vector of the temporal band n; M is a signature matrix of endmember c in the temporal band n; and e is the error term. The model revealing an unconstrained linear mixing issue (i.e., abundance sum-to-one and abundance non-negativity) can be solved using the constrained least squares (Heinz, 2001). The classification result is a composite image (values between 0−1). It was necessarily to convert the fraction of a mixed pixel to a pure pixel with respect to a desired class using the winner-take-all method. Endmembers used in this study were selected from the filtered NDVI data based on the analysis of the ground reference data and the information recorded from the field surveys. Twelve (single-cropped rain-fed rice = 2; double-cropped irrigated rice = 4; double-cropped rain-fed rice = 1; triple-cropped irrigated rice = 4; and annual crop = 1) endmembers were extracted from sampling sites (Fig. 4a).

Table 1. Classification accuracy assessment results for the 2005 SPOT data.

Classification result (pixels)

	Classification result (pixels)		
Ground reference in 2005 (pixels)	Double-cropped rice	Non-rice area	Total
Taitung study site			
Double-cropped rice	55,769	9,938	65,707
Non-rice area	5,737	178,556	184,293
Total	61,506	188,494	250,000
Producer accuracy (%)	84.9	96.9	
User accuracy (%)	90.7	94.7	
Overall accuracy (%)	93.7		
Kappa coefficient	0.84		
Chiayi study site			
Double-cropped rice	19,919	4,491	24,410
Non-rice area	4,302	33,688	38,090
Total	24,321	38,179	62,500
Producer accuracy (%)	81.6	88.4	
User accuracy (%)	81.9	88.2	
Overall accuracy (%)	85.8		
Kappa coefficient	0.70		
Taoyuan study site			
Double-cropped rice	11,282	2,745	14,027
Non-rice area	3,025	45,448	48,473
Total	14,307	48,193	62,500
Producer accuracy (%)	80.4	93.8	
User accuracy (%)	78.9	94.3	
Overall accuracy (%)	90.8		
Kappa coefficient	0.74		

3.4 Accuracy assessment

The classification results were verified in two ways: (1) the classified map (2002) was compared with the 2002 ground reference data using the error matrix, and (2) the MODIS-derived rice areas for 2002 and 2007 were compared with the government rice area statistics.

3.5 Classification results

The classification results (Figs. 4a,b) showed the distributions of the double-cropped irrigated rice, more concentrated in the upper delta, while the triple-cropped rice were concentrated in the central region. Double-cropped rainfed rice was common along the coastal areas. The single-cropped rain-fed rice was scattered across the region. The comparison results between the classified map with the ground reference map for 2002 indicated the overall accuracy of 71.6% and a Kappa coefficient of 0.6 (Table 2). The MODIS-based area estimates for 2002 and 2007 compared with the rice statistics revealed the relative errors in area of -1.9% (2002) and -2.3% (2007). In general, good agreement between the two datasets was achieved. For 2002, R2 explained 93.7% of the variance (P-value < 0.05, F-statistics = 149.9, df = 11, RMSE = 406 km2), while the same results were also achieved for 2007 (R^2 = 0.95, RMSE 379.3 km^2, P-value < 0.05, F-statistics = 203.7, df 11). From 2002 to 2007, the largest change was the conversion from the triple rice cropping to double rice cropping (29%), and about 12% of the area of double-cropped irrigated rice had been converted to triple cropping.

Fig. 3. The study area in Vietnam.

5. CONCLUSIONS

The objective of this study was to develop classification approaches for rice crop mapping in Chinese Taipei and the Vietnamese Mekong Delta. We concluded that EMD is a good filter for noise filtering of the time-series SPOT and MODIS NDVI data. The statistical approach (i.e., correlation analysis and sign-test statistic) applied to the filtered time-series SPOT NDVI data for double-cropped rice classification in Chinese Taipei demonstrated the validity of this approach. The classification results for the three study sites showed the overall accuracy and Kappa coefficient greater than 85% and 0.7, respectively. Similarly, the application of the LMM to the filtered time-series MODIS NDVI data confirmed the validity for quantification of rice cropping systems in the Mekong Delta. The overall classification accuracy was 71.6%. Strong correlations between classification results and rice statistics reaffirmed the classification results (R2>0.9 in both cases).

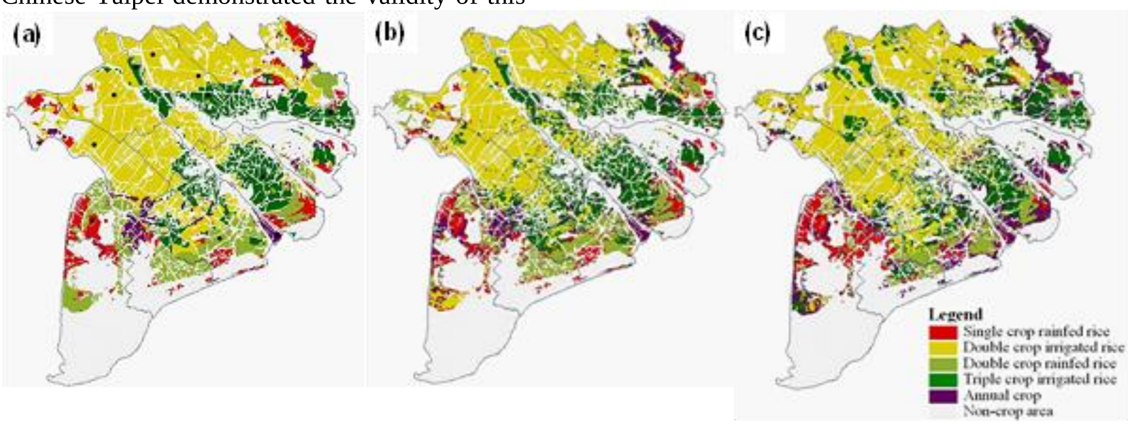


Fig. 4. The 2002 ground reference data (a) with reference to the classification results derived from MODIS data for 2002 (b) and 2007 (c). Red dots show sampling sites used to extract endmembers.

Table 2. Classification accuracy assessment results for the 2002 and 2007 MODIS data.
Classification result for 2002 (pixels)

	Classification result for 2002 (pixels)					
Ground reference in 2002 (pixels)						
Rice cropping system/ annual crop	Single crop rain-fed rice	Double crop irrigated rice	Double crop rain-fed rice	Triple crop irrigated rice	Annual crop	Total
Single-cropped rain-fed rice	15,363	1,800	3,064	1,994	8,447	30,668
Double crop irrigated rice	3,155	117,952	3,695	20,564	4,307	149,673
Double crop rain-fed rice	7,087	4,808	30,636	2,435	5,838	50,804
Triple crop irrigated rice	657	7,829	595	48,148	4,557	61,786
Annual crop	1,759	585	535	3,525	7,445	13,849
Total	28,021	132,974	38,525	76,666	30,594	306,780
Producer accuracy (%)	50.1	78.8	60.3	77.9	53.8	
User accuracy (%)	54.8	88.7	79.5	62.8	24.3	
Overall accuracy (%)	71.6					
Kappa coefficient	0.6					

REFERENCES

[1]Adams, J.B., Smith, M.O., Johnson, P.E., 1986. Spectral mixture modelling: a new analysis of rock and soil types at the Viking Lander I Site. J. Geophys. Res. 91, 10513-10513.

[2]Bolstad, P., Lillesand, T.M., 1991. Rapid maximum likelihood classification. Photogrammetric Engineering and Remote Sensing, 57, 67-74.

[3]Bridhikitti, A., Overcamp, T.J., 2012. Estimation of Southeast Asian rice paddy areas with different ecosystems from moderate-resolution satellite imagery. Agriculture, Ecosystems & Environment 146, 113-120.

[4]Chou, T.Y., Lei, T.C., Chen, H.H., 2006. Application of boosting to improve image image classification accuracy in rice parcel with decision tree, ACRS.

[5]FAO., 2002. FAO Rice information, Italy.

[6]GSO, 2007. Statistical yearbook of Vietnam, Hanoi, Vietnam.

[7]Heinz, D.C.a.C., C. I., 2001. Fully constrained least squares linear spectral mixture analysis method for material quantification in hyperspectral imagery. IEEE Transactions on Geoscience and Remote Sensing 39, 529-545.

[8]Huang, M.-Y., Huang, C.J., Fu, T.-T., 2002a. Cultivation arrangements and the cost efficiency of rice farming in Chinese Taipei. Journal of Productivity Analysis 18, 223-239.

[9]Huang, M.Y., Huang, C.J., Fu, T.T., 2002b. Cultivation arrangements and the cost efficiency of rice farming in Chinese Taipei.

[10]Huang, N.E., Shen, S.S., 2005. Hilbert-Huang transform and its applications. World Scientific.

[11]Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., H.H, S., Zheng, Q., Yen, N.C., Tung, C.C., Liu, H.H., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society London A 454, 903 – 995.

[12]Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C. and Liu, H.H., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society London A 454, 903 995.

[13]Khoa, L.V., 2003. Soil compaction of intensified rice fields in the Mekong Delta, Cantho University's scientific report, Can Tho, Vietnam.

[14]Maclean, J.L., Dawe, D. C., Hardy, B., Hettel, G. P., 2002. Rice almanac: source book for the most important economic activity on earth. CABI Publishing.

[15]Sub-NIAPP, 2002. Land-use map of the mekong delta, Vietnam.

[16]Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J.Y., Salas, W., Moore Iii, B., 2006. Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sensing of Environment 100, 95-113.

[17]Young, O.R., Steffen, W., 2009. The earth system: sustaining planetary life-support systems

[18]Principles of ecosystem stewardship, in: Chapin, F.S., Kofinas, G.P., Folke, C. (Eds.). Springer New York, pp. 295-315.

Identifying Drivers of Land Use Change in China: A Spatial Multinomial Logit Model Analysis

Man Li [1], JunJie Wu [1], Xiangzheng Deng [2]
1. Department of Agricultural and Resource Economics, Oregon State University, Corvallis, OR 97331, USA.
2. Center for Chinese Agricultural Policy, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China.
This version: November, 2011
manlichn@gmail.com

***Abstract*—This paper presents an empirical analysis of major drivers of land use change in China from 1988 to 2005. We compile a geographic information system (GIS) database on land use, weather conditions, land quality, topographic features, and economic variables and use it to estimate a land use change model. We also develop a new method to estimate a spatial multinomial logit model that explicitly takes into account the spatial interactions between land use choices. Results indicate that both economic and geophysical variables affected land use change in China. The growth of urban land value was a dominant force for farmland development and the increase in rural household income was a primary driver of returning farmland to forests and grassland. The growth of urban household income and road density led to less pressure on grassland but more on forests. Public agricultural investment contributed to farmland increase, which came largely at the expense of lands in forests and grass.**

Keywords—Land use change; spatial interaction; spatial multinomial logit regression; China

1. INTRODUCTION

China has experienced rapid urbanization in the last twenty years. The fraction of population residing in urban areas increased from 26% to 47% during the period 1990–2009 (NBSC, 2010)[In addition to permanent migrants, urban agglomeration also attracted massive so-called “floating population” (migrants without local household registration status) from rural areas, due largely to a huge demand for low-wage rural labor and a broad reservoir of the rural unemployed (Heilig, 1997)]. In particular, rapid urban expansion into fertile farmland in traditional agricultural regions such as Huang-Huai-Hai Plain, Yangtze River Delta, and Sichuan Basin is believed by many to be a major threat to China’s national food security. This concern is rooted in the fact that China is home to one-fifth of the world’s population (World Bank, 2010), but only 10% of world’s cultivatable cropland (FAO, 2008). The Chinese government established the Basic Farmland Protection Regulation (China, State Council, 1994) and revised the Land Administration Law (China, Standing Committee, 1998) to impose a set of strict administrative controls over farmland conversion, but hundreds of thousands of acres of high-quality farmland are still being converted to development each year, particularly in rapidly urbanizing regions, such as coastal regions and areas near major cities.
According to the land use database provided by Chinese Academy of Sciences (CAS), the total developed area increased by 3.3 million hectares from 1988 to 2005. Urbanization not only caused an expansion of built-up areas but also has far-reaching indirect effects on land use change. Despite the loss of fertile farmland in traditional agricultural regions, the total acreage of farmland in China increased by 2.6 million hectares from 1988 to 2005, due largely to the conversion of grassland to crop production. Grasslands are home to thousands of plant and animal species and are natural carbon sink as well. China had 303 million hectares of grassland in 1988, accounting for approximately one-third of the total national land area. By 2005, the total acreage of grassland had reduced to 291 million hectares, a 3.9% reduction. Most of this reduction occurred in farming-pasture zones of East Inner Mongolia, North China Plain, and Loess Plateau (Liu et al., 2003).

Understanding the drivers of land use change in China is useful for the design of agricultural, environmental, and land use policies. Many previous studies have made efforts to obtain such knowledge. For example, using land use inventory data and other statistics published by the China's Administration, Heilig (1997) identified five anthropogenic factors as major driving forces of land use change in China, including population growth, urbanization, industrialization, changes in lifestyles and consumption, and shifts in political and economic arrangements and institutions; Lichtenberg and Ding (2009) found that total urban area in China's coastal provinces increased with the value of urban land and budgetary government revenues and decreased with the value of agricultural land.

With the increased concerns about the quality of land use data reported by China's statistical system, more and more studies relied on satellite remote sensing data. Most of the studies focused on relatively small geographic areas, such as single counties, provinces, or regions (Deng et al., 2002, 2010, 2011; Ostwald and Chen, 2007; Seto and Kaufmann, 2003). The few studies using nationwide data examined changes in a single land use category (Deng et al., 2008), without considering competition among multiple land use alternatives, which is critical for measuring the impact of factors affecting land use decisions when multiple land use options are economically viable. One exception is Liu et al. (2003), who documented the spatial pattern of land use change in China from 1995 to 2000. A major finding of the previous studies is that both economic and geophysical variables affected land use change in China. Most previous studies, however, are not directly comparable because of inconsistent land use categories, geographic scopes, temporal dimensions, explanatory variables, or methods. We summarized some of the representative studies on China's land use change in table 1, with respect to subject area, study region, time period, the type of land use data, and major findings.

The purposes of this study are 1) to conduct a comprehensive, systematic analysis to identify the major drivers of land use conversions among six categories in China; and 2) to assess the relative importance of various economic drivers of land use changes. To achieve these objectives, this study compiles a geographic information system (GIS) database on land use, weather conditions, land quality, topographic features, and economic variables and uses it to estimate an econometric land use model, which is a spatial multinomial logit model that explicitly takes into account the spatial interaction between land use choices. It also develops a new method to estimate the model.

In the economic literature on land use, discrete choice models (Carrión-Flores and Irwin, 2004; Lewis and Plantinga, 2007; Lubowski et al., 2006; Nelson et al., 2001; Nelson and Hellerstein, 1997; Wu et al., 2004; Wu and Cho, 2007) and duration models (Irwin and Bockstael, 2002, 2004; Irwin et al., 2003) have been widely applied in recent decades. A common challenge facing these empirical studies is spatial dependence, which may arise when land uses in nearby parcels directly affect each other or are affected by the same unobserved factors. Ignoring spatial dependence will lead to biased (or inconsistent) estimates when land use choices are spatially interdependent or when the error structure is correlated over space (Anselin, 2006). However, it is technically challenging to explicitly take spatial dependence into account in a discrete dependent variable model because of heavy computational burdens, particularly when the dataset is large. Some studies attempt to solve this problem by employing a spatial sampling technique (Carrión-Flores and Irwin, 2004; Nelson and Hellerstein, 1997), others by constructing proxy variables based on neighbors and adding them to the right-hand side of the equation (Irwin and Bockstael, 2002; Nelson et al., 2001; Nelson and Hellerstein, 1997; Wu et al., 2011). But most of the previous studies ignore the potential spatial dependence[Some studies use sample plot data from the National Resources Inventory database. The data are generated by a stratified sampling routine that ensures plots are geographically dispersed].

This paper departs from previous studies in three aspects. First, this national study is based on a highly disaggregated georeferenced land use database (Landsat Thematic Mapper scenes with a spatial resolution of 30×30 m^2) that includes data for four years (1988, 1995, 2000, and 2005). Landsat images and land cover classifications were interpreted by CAS, and the average interpretative accuracy is over 97% (Deng, 2011). Longtime coverage and repeated land use decisions in this panel dataset provide even richer sources of information on land use change relative to those observed for only one period. Second, the disaggregated GIS data are able to capture spatial interactions between land use choices and spatial heterogeneity in socioeconomic conditions, weather, land quality, and topographical features. This is particularly relevant considered that land use decisions are heterogeneous and interdependent among nearby parcels. Most previous studies on China's land use typically compiled data at an aggregated level such as county. As a consequence, some of the more complex interactions between land use decisions are not captured. Third, we propose a new method for explicitly modeling spatial interaction in a multinomial logit model. The method is computationally feasible even with a large dataset.

The remainder of this paper is organized as follows: Section 2 develops the land use change model. Section 3 describes the data and section 4 reports the results. The final section offers our conclusions.

2. MODELING LAND USE CHANGE IN CHINA

In this section, we begin with discussing the landownership and land allocation in China, then develop an econometric land use model, and finally describe the estimation method.

2.1 Landownership and Land Allocation in China

To model land use change in China, one must fully understand China's land ownership. Unlike many western countries, China has no private land; land is either owned by the state or by a village collective, depending on land use types. For example, all urban land and most forests, pasture, water area, and unused land belong to the state; all farmland is collectively owned by villagers. The state retains the right to requisition farmland and other collectively owned land for urban and industrial development and other purposes. Land requisition is a unique type of land ownership transaction in China.

China's land markets are generally referred to as land use right markets, which was first introduced in Shenzhen in 1987, formally approved there on an experimental basis in 1988, and subsequently expanded to the rest of the economy in 1992 (Deng, 2005; Lichtenberg and Ding, 2009; Zhu, 2005). The constitution specifies two types of land use right markets: conveyance markets and transfer markets. The conveyance market is the primary market in which local governments lease out use rights to private entities under long-term (40–70 years) contracts. Transactions in the conveyance market for use rights involve payment of an up-front conveyance fee, which was historically set mainly by negotiation but is increasingly set by auction or tenders subject to competitive bidding (Ding, 2007; Lichtenberg and Ding, 2009). The transfer market is the secondary market in which transactions occur between land users.

Land use decisions are made by two types of agents in China—government officials (county-level or higher) and village collectives. These two types of agents have different objectives when making land use decisions. Village collectives have authority to allocate land for agriculture, rural housing, village public works, and village enterprises. Because they benefit directly from land use, it seems reasonable to assume that they seek to maximize the present value of the stream of expected net benefits from the land use. Government officials make decisions on land requisition and urban development. Many variables may affect their decisions, including political considerations and personal objectives. Lichtenberg and Ding (2009) investigated the role of economic incentives in the primary land allocation in China. They argued that as part of its process of economic liberalization in the pursuit of higher economic growth rates, China implemented a number of fiscal and governance reforms that appear to have pushed local officials to take on the role of land developers[In 1994, China implemented a comprehensive fiscal reform to decentralize its public finance: Tax revenue was reallocated in favor of the central government but at the sacrifice of local governments. This reform did not, however, change local governments' expenditure obligations. In 1998, the State Council launched the housing monetarization policy to replace the long-standing in-kind housing subsidy. This policy targeted the housing industry as “a new growth focus” through fostering the growth of related sectors, including construction, home furnishing, electricity, and home appliances, to offset the impact of the unfavorable economic environment caused by the Asian financial crisis of 1997 (Lee and Zhu, 2006). Local governments, on behalf of the state, sell land use rights and retain all profits from land transactions]. Their investigation of China’s coastal provinces provides empirical results consistent with this theory. In addition, governments are increasingly using auctions and competitive bidding to select land developers and to set conveyance fees in the primary land market. These reforms have given rise to land conversion decisions that respond to economic incentives, even though the allocation of land between urban and rural uses is determined administratively (Lichtenberg and Ding, 2009).

2.2 The Econometric Model of Land Use

Consider land use change between time *t*-1 and *t* on a parcel of land of uniform quality within a land grid, indexed by *n*; *n* = 1,…, *N*. The parcel could stay in its initial use or be converted to one of the (*J*-1) alternatives. Suppose land use decision makers (village collectives or local officials) choose land uses to maximize the present discounted value of the stream of expected net benefits from the land, and that decision makers base their expectations of future benefits on current and historic values of relevant variables. Under these simplifying assumptions, the decision rule that emerges from the related dynamic optimization problem is: Convert the parcel to land use *j* if

$$\pi_{njt} > \pi_{nkt}, \forall k \neq j, (1)$$

where π_{njt} is the net benefit from changing land use from the initial use to land use *j* at time *t*, which equals the instantaneous expected profit from use *j* in time *t* minus any current one-period expected opportunity cost of undertaking the change (Lubowski et al., 2006).

The potential net benefits from alternative land uses on a parcel, π_{njt}, depend on attributes of the parcel, such as land quality, weather conditions, and locational characteristics, as well as economic conditions in the surrounding area. Although we have data about each grid, including its average land quality, weather conditions, and shares of alternative land uses, we do not have any information about individual parcels within a grid. A standard practice in the land use modeling literature is to decompose π_{njt} into a deterministic component and a random error term:

$$\pi_{njt} = \bar{\pi}_{njt} + \varepsilon_{njt}\ , (2)$$

where the deterministic component $\bar{\pi}_{njt}$ represents the expected average net benefit from converting every parcel of grid *n* to land use *j* at time *t*, and the random error term ε_{njt} represents the deviation from the average net benefit and is often assumed to follow a normal, logit, or type-I extreme value distribution. For example, if ε_{njt} is assumed to follow the type-I extreme value distribution, a standard multinomial logit model of land use change is derived. This is the approach taken by many previous studies (see, e.g., Chomitz and Gray, 1996; Hardie and Parks, 1997; Nelson and Hellerstein, 1997)[Another econometric issue pertains to the independence from irrelevant alternatives (IIA) property of the standard multinomial logit model, i.e., the relative odds of choosing l over k are independent of the other alternatives. Some studies appeal for more general models (e.g., nested logit model and mixed logit model) to relax IIA assumption (Lubowski et al., 2006). But this approach may be infeasible for a large sample or may lead to misspecification when a particular nested or mixed logit model is specified. An alternative approach is to employ the Hausman specification test to examine IIA property. But even in a well-specified model, the Hausman test of IIA often rejects the assumption when alternatives seem distinct (Cheng and Long, 2007). In our study, it is unsatisfactory to apply the Hausman test given six land use alternatives, which requires 15 essential tests for every initial land use (6!/[2!(6-2)!] = 15). In addition, some applications to land use have demonstrated that IIA assumption is not a serious problem for empirical work (Lewis and Plantinga, 2007; Lubowski et al., 2006)].

Although a standard logit or probit model is easy to estimate, it ignores the spatial interactions between land uses on two neighboring parcels. Spatial interactions can occur for different reasons and some of the interactions (habitat fragmentation, urban sprawl) are integrated into land use decisions explicitly (Albers, 1996; Irwin and Bockstael, 2002). For example, Albers (1996) developed an economic forest management model in which the pattern of forested land creates additional value when adjacent preserved plots form minimum habitat size. Irwin and Bockstael (2002) assumed that a parcel’s value in a developed use is affected by the past land use choices on neighboring parcels. The cost of not correcting for spatial interactions is biased (or inconsistent) estimates if it induces heteroskedastic errors (Yatchew and Griliches, 1985).

In this study, we take into account spatial interactions explicitly. Because of forward-looking nature of land use decisions, we assume that net benefits from changing land use on parcels in one grid depend on net benefits from changing land use on parcels in neighboring grids. Having the same land use nearby may promote information spillovers, technology adoption, and labor market pooling, and hence generates spatial externalities. Specifically, we rewrite equation (2) as:

$$\pi_{njt} = \sum_{m \neq n} \rho_{jt} w_{nm} \pi_{mjt} + \bar{\pi}_{njt} + \varepsilon_{njt}, (3)$$

where ρ_{jt} is a spatial autoregressive parameter ($|\rho_{jt}| < 1$), representing the degree to which net benefits from land use conversion on one grid are affected by net benefits from land use conversions on neighboring girds; w_{nm} reflects the spatial relationship between land grids n and m. Such specification is often referred to in the literature as a spatial lag model (Brueckner, 2003), commonly conceptualized as the empirical counterpart to the equilibrium solution of a spatial reaction function, which, in this context, represents the best response of land use decision makers in one grid to land use changes in other land grids.

The assumption of a spatial lag model rather than a spatial error model may be disputable in some settings. The spatial error model is more appropriate in a situation where the dependent variable is affected by unobserved factors that are correlated over space. It is worthwhile to consider further the similarity between the two specifications. The spatial error model is a special case of a spatial lag model, but with additional nonlinear constraints on the parameters; the spatial lag model is a special case of a spatial error model that is nonlinear in the parameters (Anselin, 2006). While a variety of identification strategies have been suggested in the literature, the problem in the land use conversion model is complicated in ways that prevent ready adoption of these strategies (Irwin and Bockstael, 2002). As a result, it is difficult to exactly identify the interaction parameter in practice. If the spatial correlation that exists in the unobserved factors is positive on net, the empirical estimate of the interaction effect is expected to be biased in the positive direction, and vice versa. Hence, the spatial autoregressive parameter must be interpreted with caution. In the case of a multinomial logit model, an additional attraction of a spatial lag model is that it leads to a particularly tractable estimation procedure (Klier and McMillen, 2008).

Based on the economic theories and previous studies (Deng et al., 2008; Fujita, 1989; Hall, 1966; Lichtenberg and Ding, 2009), the average expected net benefits from converting every parcel of grid n to land use j at time t, $\bar{\pi}_{nt}$ is specified as

where $\mathbf{s}_{nt-1}$ is a vector of land use proportions in

$$\bar{\pi}_{njt} = \mathbf{s}_{nt-1}\boldsymbol{\beta}^{s}_{jt} + \mathbf{y}_{nt-1}\boldsymbol{\beta}^{y}_{jt} + \mathbf{z}_{nt-1}\boldsymbol{\beta}^{z}_{jt}, (4)$$

grid n at time t-1; $\mathbf{y}_{nt-1}$ is a vector of variables describing land quality, topography, and weather conditions in grid n between time t-1 and t; $\mathbf{z}_{nt-1}$ is a vector of variables describing economic characteristics of the county in which grid n is located, including land values and income in urban and rural areas, transportation costs, and public agricultural investments. Note that we use land use proportions and county characteristics at time t-1 to explain net benefits from land use change at time t, so that statistical endogeneity seems less likely (Phaff, 1999). $\boldsymbol{\beta}_{jt} = \left(\boldsymbol{\beta}^{s\prime}_{jt}, \boldsymbol{\beta}^{y\prime}_{jt}, \boldsymbol{\beta}^{z\prime}_{jt}\right)'$ is a vector of coefficients on $\mathbf{x}_{nt-1} = \left(\mathbf{s}_{nt-1}, \mathbf{y}_{nt-1}, \mathbf{z}_{nt-1}\right)'$. These coefficients are specific to the land use converted because their magnitudes depend on the sensitivity of the net benefit to the initial land use, land quality, and the economic conditions in the surrounding area. For example, the net benefit from converting a parcel of grassland to crop production is likely more sensitive to the parcel's soil quality than the net benefit from converting the parcel to urban development, which is perhaps more sensitive to the county's level of urbanization.

Equation (3) can be written in a stacked form as follows:

$$\boldsymbol{\Pi}_{jt} = \rho_{jt}\mathbf{W}\boldsymbol{\Pi}_{jt} + \mathbf{X}_{t-1}\boldsymbol{\beta}_{jt} + \boldsymbol{\varepsilon}_{jt}, (5)$$

where $\boldsymbol{\Pi}_{jt} = \left(\pi_{1jt}, \mathrm{K}, \pi_{Njt}\right)'$, $\mathbf{X}_{t-1} = \left(\mathbf{x}_{1t-1}, \mathrm{K}, \mathbf{x}_{Nt-1}\right)'$, and $\boldsymbol{\varepsilon}_{jt} = \left(\varepsilon_{1jt}, \mathrm{K}, \varepsilon_{Njt}\right)'$. We assume $\mathbf{W}$ is a row-standardized $N \times N$ first-order queen contiguity weight matrix, i.e., $\sum_{m=1}^{N} w_{nm} = 1$, $w_{nm} > 0$ if grids n and m share common borders or vertices, and w_{nm} = 0 otherwise. This assumption maintains the essential structure of a standard spatial model while facilitating the estimation of marginal effects as addressed below[With the simplification of the structure of the weight matrix to a first-order queen contiguity weight matrix and given ρ_t, it is easy to use a numerical approach to solve for $(\mathbf{I}_N - \rho_t \mathbf{W})^{-1}$ and the diagonal elements of matrix

$\left[(\mathbf{I}_N - \rho_t \mathbf{W})'(\mathbf{I}_N - \rho_t \mathbf{W})\right]^{-1}$, which are important coefficients to estimate marginal effects. Alternative structures of the weight matrix include the nearest-neighbor matrix, the binary block matrix, the distance inverse matrix, the negative exponential function, the Gaussian function, and the spherical function (Dubin, 1998)]. The reduced form of equation (4) is $\mathbf{\Pi}_{jt} = (\mathbf{I}_N - \rho_{jt}\mathbf{W})^{-1}\mathbf{X}_{t-1}\boldsymbol{\beta}_{jt} + (\mathbf{I}_N - \rho_{jt}\mathbf{W})^{-1}\boldsymbol{\varepsilon}_{jt}$, where $\mathbf{I}_N$ is an N-dimensional identity matrix. The variance-covariance matrix of $\mathbf{\Pi}_{jt}$ is proportional to $\left[(\mathbf{I}_N - \rho_{jt}\mathbf{W})'(\mathbf{I}_N - \rho_{jt}\mathbf{W})\right]^{-1}$. Let σ_{njt}^2 be the diagonal elements of matrix , and let $\mathbf{x}_{njt-1}^* = \mathbf{x}_{nt-1}\sigma_{njt}^{-1}$ and $\mathbf{X}_{jt-1}^{**} = (\mathbf{I}_N - \rho_{jt}\mathbf{W})^{-1}\mathbf{X}_{jt-1}^*$. Under the assumption analogous to the standard multinomial logit model about , the share of grid n allocated to use j at time t can be derived as follows (Klier and McMillen, 2008; Train, 2003):

$$P_{njt} = \Pr\left(\pi_{njt} > \pi_{nkt}, \forall k \neq j\right) = \frac{e^{\mathbf{x}_{njt-1}^{**}\boldsymbol{\beta}_{jt}}}{\sum_k e^{\mathbf{x}_{nkt-1}^{**}\boldsymbol{\beta}_{kt}}}. \quad (6)$$

2.3 The Estimation Method

Equation (5) defines a spatial multinomial logit regression model. When N is large, it is infeasible to estimate the model using a traditional maximum likelihood method because the likelihood function involves an N-dimensional integration. To overcome this problem, we first linearize the generalized residuals around the starting point $\rho_{jt} = 0$ and then apply the generalized method of moments (GMM). This approach was first used by Klier and McMillen (2008) to estimate a binary logit model with spatial interdependence. With the linearized model, the procedures reduce to a standard logit (that is, nonspatial) followed by two-stage least squares.

Specifically, from (5),

$$\frac{\partial P_{njt}}{\partial \boldsymbol{\beta}_{kt}} = \left[\delta(k=j) - P_{njt}\right]P_{nkt}\mathbf{x}_{nkt-1}^{**}, (7)$$

where $\delta(k=j)$ is an indicator function, which equals 1 when $k=j$ and zero otherwise;

$$\frac{\partial P_{njt}}{\partial \rho_{kt}} = \left[\delta(k=j) - P_{njt}\right]P_{nkt}\left[(\mathbf{H}_{kt})_{n\cdot}\boldsymbol{\beta}_{kt} - \frac{\mathbf{x}_{nkt-1}^{**}\boldsymbol{\beta}_{kt}}{\sigma_{nkt}^2}(\boldsymbol{\Lambda}_{kt})_{nn}\right], \quad (8)$$

where $\mathbf{H}_{kt} = (\mathbf{I}_N - \rho_{kt}\mathbf{W})^{-1}\mathbf{W}\mathbf{X}_{kt-1}^{**}$ and $\boldsymbol{\Lambda}_{kt} = (\mathbf{I}_N - \rho_{kt}\mathbf{W})^{-1}\mathbf{W}(\mathbf{I}_N - \rho_{kt}\mathbf{W})^{-1}(\mathbf{I}_N - \rho_{kt}\mathbf{W}')^{-1}$.

Note that reduces to if $\rho_{kt} = 0$, implying $(\boldsymbol{\Lambda}_{kt})_{nn} = 0$ since $w_{nn} = 0$ by definition. Therefore, when $\rho_{kt} = 0\ \forall k,t$, the gradient terms for $\boldsymbol{\beta}_{kt}$ and $\boldsymbol{\rho}_{kt}$ reduce to:

$$\frac{\partial P_{njt}}{\partial \boldsymbol{\beta}_{kt}} = \left[\delta(k=j) - P_{njt}\right]P_{nkt}\mathbf{x}_{nt-1}, (9)$$

$$\frac{\partial P_{njt}}{\partial \rho_{kt}} = \left[\delta(k=j) - P_{njt}\right]P_{nkt}(\mathbf{W}\mathbf{X}_{t-1})_{n\cdot}\boldsymbol{\beta}_{kt}, (10)$$

Let $\boldsymbol{\theta}_t = (\boldsymbol{\beta}_t, \boldsymbol{\rho}_t)'$, where $\boldsymbol{\beta}_t = \left(\boldsymbol{\beta}_{1t}', \ldots, \boldsymbol{\beta}_{J-1t}'\right)$ and $\boldsymbol{\rho}_t = (\rho_{1t}, \ldots, \rho_{J-1t})$,[To avoid redundant parameters, we set the land use J as reference and normalize βJt = 0 and ρJt = 0 .] and let the gradient terms $\mathbf{g}_{njt} = \partial P_{njt}/\partial\boldsymbol{\theta}_t$. In a multinomial logit model, the generalized residuals are:

$$u_{njt} = s_{njt} - P_{njt}, (11)$$

where s_{njt} is the share of land use j in grid n at time t. Linearizing the generalized residuals equation around the initial estimates $\boldsymbol{\theta}_t^0 = \left(\boldsymbol{\beta}_t^0, \boldsymbol{\rho}_t^0\right)'$, we have $u_{njt} \approx u_{njt}^0 - \mathbf{g}_{njt}\left(\boldsymbol{\theta}_t - \boldsymbol{\theta}_t^0\right)$, which is equivalent to:

$$u_{njt}^0 + \mathbf{g}_{njt}\boldsymbol{\theta}_t^0 \approx \mathbf{g}_{njt}\boldsymbol{\theta}_t + u_{njt}, (12)$$

Based on equations (8)–(11), the spatial multinomial logit model (5) can be estimated using the following procedure:

First, we estimate (5) by setting $\boldsymbol{\rho}_t = \mathbf{0} : \boldsymbol{\beta}_t$ is estimated consistently by a standard multinomial logit model using the maximum likelihood method. The log-likelihood function is $LL_t = \sum_n \sum_j s_{njt} \ln P_{njt}$. No matrixes need be inverted as $\left(\mathbf{I}_N - \rho_{jt}\mathbf{W}\right)^{-1} = \mathbf{I}_N$.

Second, we estimate (11) using the linearized GMM approach. Estimation includes the following steps: 1) Given the estimated parameters $\hat{\boldsymbol{\beta}}_t^0$ from the standard multinomial logit model, the initial estimates for $\boldsymbol{\theta}_t^0$ are $\boldsymbol{\theta}_t^0 = \left(\hat{\boldsymbol{\beta}}_t^0, \mathbf{0}\right)'$. Based on $\boldsymbol{\theta}_t^0$, calculate the gradient term $\mathbf{g}_{njt}$ and the generalized residuals u_{njt}^0 using (8)–(10). Then calculate $u_{njt}^0 + \mathbf{g}_{njt}\boldsymbol{\theta}_t^0$. 2) Regress $\mathbf{G}_{jt} = \left(\mathbf{g}_{1jt}', \ldots, \mathbf{g}_{Njt}'\right)'$ on instruments $\left(\mathbf{X}_{t-1}, \mathbf{W}\mathbf{X}_{t-1}, \ldots, \mathbf{W}^5\mathbf{X}_{t-1}\right)$. The predicted values are $\hat{\mathbf{G}}_{jt}$. Then regress $\left[\left(u_{11t}^0 + \mathbf{g}_{11t}\boldsymbol{\theta}_t^0\right), \ldots, \left(u_{NJ-1t}^0 + \mathbf{g}_{NJ-1t}\boldsymbol{\theta}_t^0\right)\right]'$ on $\left(\hat{\mathbf{G}}_{1t}', \ldots, \hat{\mathbf{G}}_{J-1t}'\right)'$. The coefficient estimates are estimated values of $\boldsymbol{\theta}_t$, expressed as $\hat{\boldsymbol{\theta}}_t = \left(\hat{\boldsymbol{\beta}}_t, \hat{\boldsymbol{\rho}}_t\right)'$, which are estimates for the spatial multinomial model.

Once the model is estimated, the marginal effects of the observed on land use choice can be calculated by.

$$\frac{\partial P_{njt}}{\partial \mathbf{x}_{nt-1}} = P_{njt}\left[\boldsymbol{\beta}_{jt}\sigma_{njt}^{-1}\left(\mathbf{I}_N - \rho_{jt}\mathbf{W}\right)_{nn}^{-1} - \sum_k \boldsymbol{\beta}_{kt}P_{nkt}\sigma_{nkt}^{-1}\left(\mathbf{I}_N - \rho_{kt}\mathbf{W}\right)_{nn}^{-1}\right] \tag{13}$$

3. DATA

Our study covers the whole of mainland China. Most data used in this paper were provided by CAS, including land uses, topography, climate, and socioeconomic data. A land grid is approximately 10×10 km at the equator.

CAS generated the contiguous land use data based on the U.S. Landsat Thematic Mapper/Enhanced Thematic Mapper (TM/ETM) images (Deng et al., 2006, 2008). The contiguous land use data are more desirable than dispersed sample plots in the prediction of landscape. The data are available for four time periods—the late 1980s, the mid-1990s, the late 1990s, and the middle years of the 2000–2010 decade—denoted as 1988, 1995, 2000, and 2005, respectively. CAS made visual interpretations and digitization of TM/ETM images to generate thematic maps of land uses and sorted the data with a hierarchical classification system of 25 land use classes, which were then further grouped into six aggregated classes: farmland, forests, grassland, water area, urban land, and unused land. In particular, water area is classified as land covered by natural water bodies and land with facilities for irrigation and water conservation; urban land includes land used for urban and rural settlements, industry, and transportation[In this study, we allow land to be converted from urban to non-urban use because by definition, urban land includes rural settlements]. A detailed explanation of the six aggregated land use classes is available in the appendix.

Table 2 depicts land use conversions among these classes for 1988–2005, where entries in a cell indicate the number of million hectares that were in the row land use in 1988 and column land use in 2005. The entries along the diagonal are areas where land use has not changed. Land use changes occurred mainly between farmland, forests, and grassland, and between grassland and unused land. All land uses except grassland increased. Specially, urban area expanded by 56%, the largest change in percent among the six classes. Farmland development accounted for 80% of that expansion.

Data on geophysical variables were generated from a geographical information system (GIS) database, including time-invariant data of land quality, terrain slope, and elevation. Land quality is an index of potential crop yield, originally measured at a 5 km grid at the equator. A research team from CAS using the stand-alone software of Estimation System for Land Productivity estimated the yield potential (Deng et al., 2006). Terrain slope and elevation were generated from China's digital elevation model as part of the basic CAS database.

Climate panel data were initially collected from over 600 weather stations and organized by the China Administration. The dataset includes annual precipitation and mean annual temperature from 1991 to 2005; CAS interpolated the point climate data into surface data with the method of thin-plate smoothing spline (Hartkamp et al., 1999) to get more disaggregated information for each grid. We calculate the averages and standard deviations of annual precipitation and mean annual temperature for each conversion period. The standard deviations measure temporal variations in weather. We assume these estimated means and standard derivations are constant through every short transition period (1988–1995, 1995–2000, and 2000–2005).

There are no official data available for measuring marginal land values. Following Lichtenberg and Ding (2009), we use GDP per unit of land in their place. Data on county GDP for three years (1989, 1996, and 2000) are gathered from NBSC (2001). GDP consists of three sectors: primary, secondary, and tertiary industries. Primary industry is composed of farming, forestry, animal husbandry, and fishery. Secondary industry mainly includes activities of building, mining, manufacture, electricity and gas production. Those not belonging to the former two are classified into tertiary industry, e.g., transportation, trade, finance, education, public service, etc. For convenience, we refer to GDP in primary sector as *agricultural GDP* and refer to GDP in industry and service sectors as *urban GDP*. We use urban GDP per unit of urban area (hereafter urban GDP per hectare) as a measure of urban land value. It would be desirable to separate agricultural GDP in farming sector from that generated from forestry and other agricultural sectors, but such data are unavailable. Lacking better data, we use agricultural GDP per unit of farmland (hereafter agricultural GDP per hectare) as a measure of agricultural land value for each county and each year. Besides, agricultural GDP per hectare can be viewed as an indirect measure of proximity to urban areas. As suggested by Seto and Kaufmann (2003), people inhabit the most productive areas and hence urban development occurs first there.

Data on public agricultural investment were collected from province- and county-level statistical yearbooks and are available for four years (1994, 1995, 1999, and 2000). The investments came from state and local governments and were used mainly for developing agriculture infrastructure such as seeds, fertilizers, and irrigation projects. We use the investments in 1994, the average of investments in 1995 and 1999, and investments in 2000 when explaining land use change during the three periods (1988–1995, 1995–2000, and 2000–2005), respectively.

We also include measures of per capita income in urban and rural areas. For this purpose, we collected data on population including rural and non-rural residents from MPSC (1996, 2001). Urban income is calculated as urban GDP per non-rural resident (hereafter urban GDP per capita). A higher value of urban income could increase the demand for housing in an urban area and raise the urban land rent consequently (Fujita 1989). Rural income is calculated as agricultural GDP per rural resident (hereafter rural GDP per capita). Rural income, to a large extent, is determined by the marginal wage rate in urban areas. When the marginal wage rate increases in urban areas, more rural labor will migrate to cities to work.

We use road density as a measure of transportation costs. Based on a digital map of transportation networks in the mid-1990s, road density is calculated as the total length of all highways, national expressways, provincial-level roads, and other minor roads in a county divided by the land area of that county. County road density is available only for the mid-1990s. As a supplement, we collected provincial road length for three years (1988, 1995, and 2000) to calculate the province-level growth rate of road length. Lacking better data, we use the county road density in 1995 and the provincial growth rate to extrapolate the road density in 1988 and 2000 for each county.

Because we could not determine exactly when land use changes occurred during a time interval, we use the 1988–1989, the mid-1990s, and 2000 data (except public agricultural investment) to control for the initial land use for the three respective transition periods. The lagged measures help to reduce endogeneity. A common suggestion is that the placement of road network is endogenous. The model assumes that road density is exogenous to land use. This assumption is reasonable in some applications, especially when roads are installed for political reasons (Chomitz and Gray, 1996). China, for instance, invested approximately US$600 billion to upgrade its road system between 1990 and 2005. The road network was designed to eventually connect all cities of more than 200,000 people and its construction aimed at improving trade facilitation and promoting faster development of China's poorer inland regions (Roberts et al., 2010). Hence the placement of roads was more likely influenced by the national development strategy rather than urban or agricultural returns.

All value variables are measured at the 2000 real Chinese yuan (¥) and at the county level. Missing data reduced the usable sample to 2,034 county- and 68,918 grid-level observations for each of three time intervals (1988–1995, 1995–2000, and 2000–2005)[We eliminated Tibet Autonomous Region that is covered mainly by grassland and unused land from the dataset due to severely incomplete economic observations. Nevertheless, it will not change the fundamental results derived from this study because Tibet is a plateau region characterized by sparse population, subsistence agriculture, and less-developed economy. The land use change in Tibet is trivial in the sample period of this study]. Table 3 provides summary statistics for these variables.

4.RESULTS

The spatial multinomial logit model is estimated separately using the three-period panel data described in the last section and using the cross-sectional data for each of three conversion periods: 1988–1995, 1995–2000, and 2000–2005. Variations are relatively large between estimates from two versions of model and among estimates from the three cross-sectional analyses themselves, suggesting there might be some changes in the structure (coefficients) of land use model over time. Since these changes cannot be fully identified in the model due to limited data, we discuss the results below based on the cross-sectional analysis.

4.1 Model Performance

Table 4 reports spatial autoregressive parameter estimates by land use and time period. Almost all of them are statistically different from zero at the 1% level. This provides evidence that land use decisions in neighboring grids interact with each other. The magnitudes of the autoregressive parameters indicate that overtime, non-urban land uses became less dependent on land use in neighboring grids, while urban land use became more dependent on land use in neighboring grids. This result is consistent with the observation that land use decisions in China have become more responsive to economic incentives because returns to urban land use are more likely to be affected by the surrounding land use due to agglomeration effects and other spatial externalities.

In a GMM regression, R^2 does not have a statistical interpretation. Therefore, we evaluate the performance of the model through its prediction accuracy. First, following the winner-take-all principle, we assign each grid to the use with the highest predicted probability. We then compare the predicted use with the observed use and report two measures of prediction accuracy in table 5. One measure is "hit rates by actual use," which are the percentages of grids whose observed uses are correctly predicted. The other is "hit rates by predicted use," which are the percentages of grids whose predicted uses are confirmed by observation. Based on the two measures of prediction accuracy, the model performs quite well for the three periods. The hit rates are 80% or better for all land use categories except urban land, which has hit rates of 74%, 79%, and 74% by actual use and of 68%, 65%, and 71% by predicted use. The hit rate by actual use is higher than the hit rate by predicted use because the model over predicts urban land use. A parcel could be assigned to a use with a relatively low predicted probability, if the estimated probabilities for the other uses are even smaller. To assess the predictive power, we calculate the summary statistics for the predicted probabilities by time period and predicted land use. As shown in table 5, the mean of predicted probability is greater than 0.55 in a sample of each use except urban land; the mean value is even higher in the unused land and forests samples. Besides, the maximum of predicted probability exceeds 0.94 in every predicted land use sample, implying that the model has the strength of identifying locations in that category. In summary, accuracy measures reported in table 5 suggest that the model has strong in-sample predictive power at both aggregated and disaggregated levels.

4.2 Drivers of Land Use Change in China

Given that our main interest here is to identify the drivers of land use change, we report the estimated marginal effects. The coefficient estimates for the three models are presented in the appendix. We group all observations into six subsamples by the initial land use in each transition period and evaluate the marginal effects at the sample means for each group using equation (12). Tables 6–8 report the results for the initial land use that was farmland, forests, and grassland, respectively, for the period of 2000–2005. The results for the other two periods are reported in the appendix.

Most of the marginal effects are statistically significant at the 1% level. Farmland with a higher yield potential, as measured by the land quality variable, was more likely to stay in agricultural use and less likely to be converted to forests and grassland in the first and second periods (1988–1995; 1995–2000), as reflected by the opposite signs of the corresponding marginal effects of land quality. However, the land quality variable became less significant in the third period (2000–2005). Farmland with higher elevation was more likely to be converted to forests and grassland and less likely to stay in farm use or be developed for urban use. Farmland with steeper slope was more likely to be converted to forestland.

There is evidence that land use change was affected by weather. Farmland was less likely to be converted to grassland and unused land in areas with higher precipitation. Farmland was more likely to stay in agricultural use in those places during the first two periods. This may be because as precipitation increased, farmers found it profitable to switch from irrigation to rainfed agriculture and thus irrigation costs were saved (Wang et al., 2009). Farmland was more likely to stay in farm use and less likely to be converted to forests in areas with higher temperature. There is empirical evidence that warming was harmful to rainfed crops but beneficial to irrigated agriculture in China (Tao et al., 2008; Wang et al., 2009; You et al., 2009). Wang et al. (2009) attributed such observation to that irrigated farmer can use water to offset the heat. The marginal effects of variations in precipitation and temperature on the probability of farmland conversion changed over time. For instance, farmland in areas with a higher variation in precipitation was less likely to stay in farm use and more likely to be converted to forests and grassland during 1988–2000, while the opposite was found during 2000–2005. This may reflect the increasing adaptabilities of farmers to climate change over time[Although the estimated effects of precipitation and temperature on farmland conversions in China are generally in line with previous studies, they must be interpreted with caution since the knowledge on those effects on crop productivity remains inconclusive in the literature].

The marginal effects of road density reported in table 6 indicate that farmland in areas with a higher road density was more likely to stay in agricultural use or be developed to urban use and less likely to be converted to forests. This result may reflect that areas with higher road density have lower transportation costs and more convenient access to consumers of agricultural and industrial products and commercial services. Other things being equal, profits from urban and agricultural land uses would be larger.

The signs of the marginal effects of urban land value, urban and rural income, and public agricultural investments became increasingly consistent with economic theory over time. This provides additional evidence that land use decisions in China have been progressively responsive to economic incentives because of government reforms. During 1995–2005, farmland was less likely to stay in farm use and more likely to be converted to urban use in counties with higher urban land value. This result conforms to

Lichtenberg and Ding (2009), and may reflect that if urban land values are much higher than farmland values, local governments are more likely to approve farmland requisition. In addition, local governmental officials in those places are more likely to engage in political games to increase their promotion opportunities, which often involve public investments in "image projects" designed to show off their "political achievements." Those "image projects" often require conversions of large amounts of farmland into governmental, commercial, and industrial uses.

The marginal effects of agricultural land value on the probability of farmland conversion varied over time. From 1988 to1995, farmland was less likely to stay in farm use and more likely to be converted to urban use in counties with higher agricultural land value. This result is consistent with the findings from a case study on China's Pearl River Delta for 1988–1996 by Seto and Kaufman (2003), who attributed this pattern in part to migration—migrants tended to move to the areas with high farmland productivity and therefore urban centers emerged from those regions. In contrast to the first period, agricultural land value has statistically insignificant effects on farmland conversion in the second and third periods. Similar results were found in Lichtenberg and Ding (2009), who studied urban development in 10 coastal provinces in China from 1996 to 2004. This may be viewed as the impacts of the first migrants versus later immigrants. China accelerated the pace of urbanization since the early 1990s. First migrants were more likely to occupy areas with high farmland productivity than later immigrants. Consequently, urban development occurred first in the most productive regions in the beginning of urbanization (i.e., the first period) but the location of urban centers was less and less sensitive to land productivity.

Not surprisingly, a higher level of urban GDP per capita, as a proxy for urban income, increased the probability of farmland being converted to urban use and decreased the probability of farmland being converted to forests, grassland, and unused land. The marginal effects of this variable on the likelihood of farmland staying in its initial use changed over time. For example, the marginal values are estimated to be positive in the first two periods and negative in the last period, which reflects land development is increasingly dominated by market mechanisms.

Rural income also affects the probability of farmland conversions. Farmland was less likely to stay in agricultural use and more likely to be converted to forests, grassland, and watered areas in counties with higher rural income. This may reflect that rural income is an indirect measure of the marginal wage rate of urban labors as well. In China, traditional farming is a low-payoff activity. Farmers in counties with higher marginal wage rate of urban labors have more financial incentives to switch their livelihood strategies from encroaching into forests and grassland to off-farm employment, including rural-to-urban migration. Such changes may cause conversions of some farmland to forests and grassland.

Public agricultural investment is a government strategy for promoting agricultural development and increase agricultural productivity. The strategy is shown to reduce the conversions of farmland to forests and grassland. The results also show that areas with larger public agricultural investment tended to face greater pressure for farmland development.

Tables 7 and 8 present the marginal effects of various variables on forests and grassland conversions. Forests and grassland with higher yield potentials were more likely to be converted to farmland. Forests with steeper slopes were more likely to stay forested and less likely to be converted to farmland and grassland. Grassland with higher elevation was more likely to stay pastured and less likely to be converted to farmland and forests.

Forests and grassland were more likely to be converted to farmland in areas with higher road density. Forests were also more likely to be converted to grassland and less likely to stay forested in those places. There is a large body of literature which showed that building and upgrading roads led to deforestation (Chomitz and Gray, 1996; Cropper et al., 1999; Pfaff, 1999). One noticeable exception is Deng et al. (2011), which found that road development in China's Jiangxi province had no impacts on the total forested acreage during the period of 1995–2000.

Forests and grassland were more likely to be converted to unused land in counties with higher urban land value and to be developed for urban use in counties with higher urban income. Forests were less likely to be converted to farmland but more likely to be converted to grassland in counties with higher rural income; grassland was more likely to stay pastured and less likely to be converted to farmland and forests in those places. Public agricultural investment is found to increase the conversion of forests and grassland to farmland except that in the first period.

4.3 Relative Importance of Alternative Drivers of Land Use Changes

Although the marginal effects reveal which variables are statistically significant in affecting land use change in China, they do not show their relative importance. To provide some sense of the relative importance of alternative forces driving land use change in China, we use the empirical models to estimate land use changes that would occur under a baseline and six counterfactual scenarios from 1988 to 2005. As described in table 9, the baseline simulation uses historical observations; it provides a benchmark to measure land use changes under counterfactual scenarios; the counterfactual scenarios respectively hold urban land value, agricultural land value, urban income, rural income, road density, and public agricultural investment at a hypothetical level and keep the remaining variables at their historically observed values.

Change in land use between 1988 and 2005 under each of the seven scenarios is estimated using the following steps: 1) Predicting probabilities of land use for each grid based on the land use in 1988 and determining the land use shares on each grid in 1995; 2) repeat the procedure for the periods 1995–2000 and 2000–2005 to determine the land use shares on each grid in 2005; 3) compare land use shares between 1988 and 2005 on each grid to determine the land use change under the scenario. The simulation results are reported in table 10, where the odd columns report the simulated land use changes (million hectares); the even columns report percentage changes from the baseline[Note that percentage changes under the six counterfactual scenarios cannot add up to 100%. This method follows Stavins and Jaffe (1990). Percentage changes can be interpreted as the share of land use change attributed to the factor]. A positive percentage change indicates that the increase is larger or the decrease is smaller relative to the baseline. A negative percentage change indicates the opposite. Comparing the magnitudes of these values across rows provides an estimate of the relative importance of different factors affecting national land use.

The direction of the acreage change in the baseline conforms to the direction of actual change, except for forest acreage. The baseline changes range from -11 million hectares to 10 million hectares; by comparison, the actual changes range from -11 million hectares to 5 million hectares. The discrepancies between the baseline change and the actual change are small (within 0.9 million hectares) in farmland, grassland, water, and urban uses but are relatively large in forests and unused land. The model tends to underestimate forests and overestimate unused land.

The results suggest that farmland conversions were mostly driven by increasing urban land value and rising rural income. The average urban land value and rural income were, respectively, ¥56,000 per hectare and ¥1,150 per capita in 1989. By 2000, the amounts had increased to ¥186,000 per hectare and ¥1,870 per capita. Without the growth in urban land value, there would have been 1.6 million hectares more of farmland; without the increase in rural income, there would have been 1.8 million hectares more of farmland. In other words, the increases in urban land value and rural income accounted for more than 80% of the change in total farmland acreage in the baseline.Increasing road density is found important in driving farmland expansion. From 1989 to 2000, the average county-level road density increased from 0.751 meter/hectare to 1.043 meter/hectare. With this growth, farmland increased by 0.7 million hectares, accounting for 34% of the total farmland increase in the baseline. Public agricultural investment was another driver of farmland expansion. With an approximate annual average of ¥82,000 investment in agriculture per county, farmland increased by 0.2 million hectares, accounting for 11% of the total farmland increase in the baseline.

The growths of urban income and urban land value are shown as primary drivers of urban development. From 1989 to 2000, the average county-level urban income increased from ¥8,870 per capita to ¥22,160 per capita; with this growth, urban area increased by 0.6 million hectares, accounting for 17% of the increase in total urban area under the baseline. With the growth in urban land value, urban area increased by 0.4 million hectares, accounting for 11% of the increase in total urban area under the baseline. Road network development also played relatively small, but positive roles in urban expansion.

The results suggest that deforestation was primarily driven by increasing road density and rising urban income. Without these increases, there would have been 0.8 and 0.4 million hectares more of forestland, accounting for 18% and 10% of the change in total forested area under the baseline. Surprisingly, both factors are found to help alleviate grassland loss. In particular, the growth in urban income abated grassland loss by 3.8 million hectares, accounting for 34% of the change in total grassland under the baseline. This may be because road network development and rising urban income played a role of "pressure valve" in grassland conversion. In a region with faster economic growth or easier access to the outside world, rural households who previously relied on encroaching into grassland may seek off-farm employment, which released pressure on grassland conversions.

Rising rural income also acted as a "pressure valve" for forestland and grassland conversions. With the growth in this factor, forestland increased by 0.5 million hectares and grassland increased by 2 million hectares, which accounted for 10% and 18% of the changes in forested and grass areas under the baseline. In contrast, public agricultural investment is shown to enhance the pressure on forested and grass areas. Without the investment, there would have been 0.3 million hectares more of forestland and 1.1 million hectares more of grassland, accounting for 7% and 10% of the changes in forested and grass areas under the baseline.

5.CONCLUSIONS

This paper presents an empirical analysis of major drivers of land use change in China from 1988 to 2005. We compile a geographic information system (GIS) database on land use, weather conditions, land quality, topographic features, and economic variables and use it to estimate a land use change model. We also develop a new method to estimate a spatial multinomial logit model that explicitly takes into account the spatial interactions between land use choices.

Results indicate that increasing urban land value was a major driver of farmland development because land use decisions in China have been progressively responsive to economic forces. Rising rural income was a primary driver of conversions of farmland to forests and grassland, which may reflect that rural income was in part, determined by the marginal wage rate in urban areas. As the marginal wage rate increased in urban areas, farmers found it profitable to migrate to cities to work and hence converted some farmland back to forests and grassland. The growth of urban income and road density led to less pressure on grassland but more on forests. This may be because in a region with improved economic viability, farmers were likely to switch their livelihood strategy from encroaching into grassland to off-farm employment. Public agricultural investment, as a government strategy for promoting agricultural development and increase agricultural productivity, contributed to farmland increase that came largely at the expense of lands in forests and grass.

Geophysical variables also affect land use change in China. Other things being equal, farmland with a higher yield potential and lower elevation was more likely to stay in farm use and less likely to be converted to forests and grassland. Forests with smaller slope and grassland with lower elevation were less likely to stay in their original uses and more likely to be converted to the other two. Farmland was less likely to be converted to grassland and unused land in areas with higher precipitation and to be converted to forests in areas with higher temperature. Farmland was also more likely stay in farm use in those places, which can be partly viewed as farmers' adaptation to climate change, e.g., irrigated farmers may switch to rainfed agriculture in areas with higher precipitation and use water to counteract the heat in areas with higher temperature.

This big-picture study omits many details. For example, we do not take into account policy changes explicitly due to the lack of data. The six counterfactual simulations use hypothetical values outside the sample. The results must be interpreted with caution. Nonetheless, the results of this study may help policymakers make more informed decisions. Driven by fast economic growth, urban land value in many regions of China has been highly appreciated. Expanding facilities for industrial parks, commercial buildings, transportation infrastructure, and energy generation are consuming a large amount of arable land, which has brought it with considerable attention to China's food security. As Heilig (1997) pointed out, future land use in China depends heavily on how the economy's leaders pursue reform. As land development is increasingly dominated by market mechanisms, local government officials and village collective leaders would make key decisions on land allocation. Incentive-based policies that encourage these decision makers to take on the role of conservationists, instead of land developer, will likely be more effective for farmland conservation than the traditional command and control approaches.

Public agricultural investment helps reduce farmland loss but has negative side-effects on forests and pasture. As is well recognized, protecting forests and grassland in ecologically sensitive areas is of paramount importance from an environmental conservation perspective. Increasing rural income apparently helps achieve this purpose by providing farmers financial incentives to switch their livelihood strategies to off-farm employment. An ongoing practice in China is Sloping Land Conversion Program (SLCP), initiated in 1999 and designed with dual goals of ecological restoration and poverty alleviation by paying farmers to increase forest cover on highly erodible cropland (typically sloped land). Such practice is often called payments for ecosystem service (PES). Although the goals of SLCP are ambiguous, evidence has suggested that participants shifted their labor endowment from on-farm work to off-farm labor market (Kelly, 2010; Uchida et al., 2009). It should be noted that the strategy of increasing rural income includes but not limited to PES programs. Any practices that may promote rural development and encourage farmers to move into off-farm employment could be considered.

In the pursuit of "new economic growth focus", the central government has targeted construction and automotive sectors as its "pillar industries". This, along with its national development strategy to facilitate domestic trade and to narrow down regional disparities, required fast development of road network. China invested approximately US$40 billion per year to upgrade its road system during 1988–2009. This investment has led to an increase in the total road length by 2.9 million kilometers, almost a threefold increase compared to the road length of 1 million kilometers in 1988 (NBSC, 2001–2010, 2005). Building roads through, near, or to forests and grassland may improve the economic viability in the area, but it has opposite effects on the two types of lands. It relieves pressure on grassland but imposes pressure on forests. Hence, caution must be taken when designing and upgrading road network in the forested area and in the mosaic area with forest/grass cover.

ACKNOWLEDGEMENTS

This paper is based on Man's PhD dissertation work at Oregon State University. The authors acknowledge financial support from the Department of Agricultural and Resource Economics, Oregon State University. The authors also wish to thank the National Key Programme for Developing Basic Science of China (2010CB950904) and the National Science Foundation of China (41171434) for the financial support to generate the dataset used in this study.

REFERENCES

[1] Albers, H.,1996.Modeling ecological constraints on tropical forest management: spatial interdepence, irreversibility, and uncertainty, Journal of Environmental Economics and Management, 30: 73–94.

[2] Anselin, L.,2006.Spatial econometrics, In T. Mills and P. K. (eds) Palgrave Handbook of Econometrics: Volume 1, Econometric Theory. Basingstoke: Palgrave Macmillan.

[3] Brueckner, J.,2003.Strategic interaction among governments: An overview of empirical studies, International Regional Science Review, 26: 175–188.

[4] Carrión-Flores, C., Irwin, E.G.,2004.Determinants of residential land-use conversion and sprawl at the rural-urban fringe, American Journal of Agricultural Economics, 86: 889–904.

[5] Cheng, S., Long, J.S.,2007.Testing for IIA in the multinomial logit model, Sociological Methods and Research, 35: 583–600.

[6] Chomitz, K., Gray, D.,1996.Roads, land use, and deforestation: A spatial model applied to Belize, The World Bank Economic Review, 10: 487–512.

[7] Cropper, M., Griffiths, C., Mani, M.,1999.Roads, population pressures, and deforestation in Thailand, 1976–1989, Land Economics, 75: 58–73.

[8] Deng, F.,2005. Public land leasing and the changing roles of local government in China, Annals of Regional Science, 39:353–373.

[9] Deng, X., Huang, J., Rozelle, S., Uchida, E.,2006. Cultivated land conversion and potential agricultural productivity in China, Land Use Policy, 23: 372–384.

[10] ________ ,2008. Growth, population and industrialization, and urban land expansion of China, Journal of Urban Economics, 63: 96–115.

[11] Deng, X., Huang, J., Uchida, E., Rozelle, S.,2011. Pressure cookers or pressure valves: Do roads lead to deforestation in China? Journal of Environmental Economics and Management, 61:79–94.

[12] Deng, X., Jiang, Q., Zhan, J., He, S., Lin, Y.,2010. Simulation on the dynamics of forest area changes in Northeast China, Journal of Geographical Sciences, 20: 495–509.

[13] Deng, X., Liu, J., Zhuang, D., Zhan, J., Zhao, T.,2002. Modeling the relationship of land use change and some geophysical indicators for the interlock area of farming and pasturing in China, Journal of Geographical Sciences, 12: 397–404.

[14] Ding, C.,2007.Policy and praxis of land acquisition in China, Land Use Policy, 24: 1–13.

[15] Dubin, R.A.,1998.Spatial autocorrelation: A primer, Journal of Housing Economics, 7: 304–327.

[16] Food and Agriculture Organization of the United Nations ,2008. FAOSTAT, ResourceSTAT, http://faostat.fao.org/site/377/default.aspx#ancor (accessed September 3, 2010.

[17] Fujita, M.,1989.Urban economic theory: land use and city size, 1st ed. New York: Cambridge.

[18] Hall, P. (ed.),1966. Von Thünen’s Isolated State: An English edition of der iIsolierte staat by johann heinrich von thünen, 1st ed. Pergamon Press.

[19] Hardie, I., Parks, P. ,1997.Land use with heterogeneous land quality: An application of an area base model, American Journal of Agricultural Economics, 79: 299–310.

[20] Hartkamp, A.D., Beurs, K.D., Stein, A., White, J.W.,1999. Interpolation techniques for climate variables, Working paper, International Maize and Wheat Improvement Center, Mexico.

[21] Heilig, G.,1997. Anthropogenic factors in land-use change in China, Population and Development Review, 21: 139–168.

[22] Irwin, E., Bockstael, N.,2002.Interacting agents, spatial externalities and the evolution of reisidential land use patterns, Journal of Economic Geography, 2: 31–54.

[23] ________,2004.Land use externalities, open space preservation, and urban sprawl, Regional Science and Urban Economics, 34: 705–725.

[24] Irwin, E., Bell, K., Geoghegan, J.,2003.Modeling and managing urban growth at the rural-urban fringe: A parcel-level model of residential land use change, Agricultural and Resource Economics Review, 32: 83–102.

[25] Kelly, P.,2010.Land retirement and non-farm labor market participation: An analysis of China’s Sloping Land Conversion Program, Working paper, University of California, Berkeley.

[26] Klier, T., McMillen, D.P.,2008.Clustering of auto supplier plants in the United States: Generalized method of moments spatial logit for large samples, Journal of Business and Economic Statistics, 26: 460–471.

[27] Lee, J., Zhu, Y.,2006.Urban governance, neoliberalism and housing reform in China, The Pacific Review, 19:39–61.

[28] Lewis, D.J., Plantinga, A.J.,2007.Policies for habitat fragmentation: Combining econometrics with GIS-based landscape simulations, Land Economics, 83: 109–127.

[29] Lichtenberg, E., Ding, C.,2009. Local officials as land developers: Urban spatial expansion in China, Journal of Urban Economics, 66: 57–64.

[30] Liu, J., Liu, M., Zhuang, D., Zhang, Z., Deng, X. ,2003.Study on spatial pattern of land-use change in China during 1995–2000, Science in China (Series D), 46: 373–384.

[31] Lubowski, R.N., Plantinga, A.J., Stavins, R.N.,2006.Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function, Journal of Environmental Economics and Management, 51: 135–152.

[32] Ministry of Public Security of China,1996. China Counties and Cities Population Yearbook, Beijing: Chinese Public Security University Press.

[33] ________ ,2001.China Counties and Cities Population Yearbook, Beijing: Chinese Public Security University Press.

[34] NBSC (National Bureau of Statistics of China) (2001–2010) China Statistical Yearbook, Beijing: China Statistical Press.

[35] ________,2005.Comprehensive Statistical Data and Materials on 55 Years of New China, Beijing: China Statistical Press.

[36] Nelson, G.C., Harris,V., Stone, S.W.,2001. Deforestation, land use, and property rights: Empirical evidence from Darién, Panama, Land Economics, 77: 187–205.

[37] Nelson, G.C., Hellerstein, D.,1997.Do roads cause deforestation? Using satellite images in econometric analysis of land use, American Journal of Agricultural Economics, 79: 80–88.

[38] Ostwald, M., Chen, D. ,2006. Land-use change: Impacts of climate variations and policies among small-scale farmers in the Loess Plateau, China, Land Use Policy, 23: 361–371.

[39] Pfaff, A.,1999.What drives deforestation in the Brazilian Amazon? Evidence from satellite and socioeconomic data, Journal of Environmental Economics and Management 37: 26–43.

[40] Roberts, M., Deichmann, U., Fingleton, B., Shi, T.,2010. On the road to prosperity? The economic geography of China’s national expressway network, Policy Research Working Paper 5479, Washington, DC: The World Bank.

[41] Seto, K.C., Kaufmann, R.K.,2003.Modeling the drivers of urban land use change in the Pearl River Delta, China: Integrating remote sensing with socioeconomic data, Land Economics, 79: 106–121.

[42] Stavins, R., Jaffe, A.,1990. Unintended impacts of public investments on private decisions: The depletion of forested wetlands, The American Economic Review, 80: 337–352.

[43] Tao, F., Yokozawa, M., Liu, J., Zhang, Z.,2008. Climate-crop yield relationships at provincial scales in

[44] China and the impacts of recent climate trends, Climate Research, 38: 83–94.

[45] The Standing Committee of the Ninth National People's Congress of the People's Republic of China, 1998. Land Administration Law of the People's Republic of China (first amended version).

[46] The State Council of the People's Republic of China ,1994. Basic Farmland Protection Regulation.

[47] Train, K.E.,2003.Discrete choice methods with simulation, New York: Cambridge University Press.

[48] Uchida, E., Rozelle, S., Xu, J.,2009.Conservation payments, liquidity constraints, and off-farm labor: Impact of the Grain-for-Green program on rural households in China, American Journal of Agricultural Economics, 91: 70–86.

[49] Wang, J., Mendelsohn, R., Dinar,A., Huang, J., Rozelle, S., Zhang, L.,2009.The impact of climate change on China's agriculture, Agricultural Economics, 40: 323–337.

[50] World Bank,2010.World development indicators database, http://data.worldbank.org/indicator/SP.POP.TOTL (accessed September 3, 2010).

[51] Wu, J., Adams, R.M., Kling, C.L., Tanaka, K.,2004.From microlevel decisions to landscape changes: An assessment of agricultural conservation policies, American Journal of Agricultural Economics, 86: 26–41.

[52] Wu, J., Cho, S.H.,2007.The effect of local land use regulations on urban development in the Western United States, Regional Science and Urban Economics, 37: 69–86.

[53] Wu, J., Fisher, M., Pascual, U.,2011.Urbanization and the viability of local agricultural economies, Land Economics, 87: 109–125.

[54] Yatchew, A., Griliches, Z.,1985.Specification error in probit models, The Review of Economics and Statistics, 67: 134–139.

[55] You, L., Rosegrant, M., Wood, S., Sun, D.,2009. Impact of growing season temperature on wheat productivity in China, Agricultural and Forest Meteorology, 149: 1009–1014.

[56] Zhu, J.,2005.A transitional institution for emerging land markets in China, Urban Studies, 8: 1369–1390.

Table 1. Summary of Some Studies on Land Use Change in China

Study	Subject area	Study region	Study period	Land Use Data type	Some findings
Heilig (1997)	Multiple LUC	China	1985-1995	Inventory data published by the China Adminitration	Document five anthropogenic drivers of LUC, including population growth, urbanization, industrialization, changes in lifestyles and consumption, and shifts in political and economic arrangements and institutions
Deng et al. (2002)	Multiple LUC	Interlock area of farming and pasturing in northern China	1990-2000	Remotely sensed data from TM/ETM images	Geophysical conditions have great impact on grassland conversions
Liu et al. (2003)	Multiple LUC	China	1995-2000	Remotely sensed data from TM/ETM images	Document the pattern and regional differention on LUC
Ostwald and Chen (2007)	Multiple LUC	Ansai county, Shaanxi province, China	2000-2002	Remotely sensed data from MODIS/ASTER images	Policy and economics drives LUC directly; climatic has some impact on regional scale vegetation pattern
Seto and Kaufmann (2003)	Urban land expansion	Pearl River Delta, Guangdong province, China	1988-1996	Remotely sensed data from TM/ETM images	Drivers of ag. land conversion to urban use include the ratio of ag. land productivity to industrial land productivity, forest direct investment, ag. labor productivity, and wage
Deng et al. (2008)	Urban land expansion	China	1988-2000	Remotely sensed data from TM/ETM images	Economic (GDP) growth drives urban land expansion
Lichtenberg and Ding (2009)	Urban land expansion	10 coastal provinces, China	1996-2004	Inventory data published by the China Adminitration	Urban area changes increased with urban land value and budeitary government revenues and decreased with ag. land value
Deng et al. (2010)	Forestland change	Northeast China	1988-2005	Remotely sensed data from TM/ETM images	Forest area changes increased with gross forestry output, forest protection projects, ag. population proportion, and decreased with forestry production and population density
Deng et al. (2011)	Deforestation	Jiangxi Province, China	1995-2000	Remotely sensed data from TM/ETM images	Roads have no impact on the level of forests and the rate of deforestation

Table 2. Remotely Sensed Land Use Conversions in China, 1988–2005

Land use in 1988	Land use in 2005 Farm	Forest	Grass	Water	Urban	Unused	Total	Unchanged
Farm	**169.0**	3.4	3.5	1.1	2.8	0.6	180.3	94%
Forest	5.2	**225.5**	4.8	0.2	0.3	0.9	236.9	95%
Grass	7.5	8.5	**277.6**	0.5	0.3	10.3	304.6	91%
Water	0.8	0.2	0.5	**20.4**	0.2	0.9	23.0	89%
Urban	0.5	0.1	0.1	0.2	**4.4**	0.0	5.2	85%
Unused	1.8	0.6	5.7	1.0	0.2	**189.8**	199.1	95%
Total	184.7	238.2	292.2	23.3	8.2	202.5	949.1	n.a

Note: Entries in a cell indicate the number of million hectares that were in the row land use in 1988 and column land use in 2005. The entries along the diagonal are areas where land use has not changed.
Source: Remote sensing database, Chinese Academy of Science.

Table 3. Summary Statistics of Explanatory Variables

Variable	Measurement Unit	N	Mean	Std. Dev.	Minimum	Maximum
10-km-gird level						
Land quality	1000 kg/ha.	68918	1.728	2.807	0.000	14.168
Terrain slope	degree	68918	3.091	4.154	0.000	66.250
Elevation	km	68918	1.333	1.342	-0.153	6.444
Precipitation, 1991-1995	1000 mm	68918	0.540	0.442	0.007	1.877
Precipitation, 1996-2000	1000 mm	68918	0.547	0.461	0.006	1.824
Precipitation, 2001-2005	1000 mm	68918	0.681	0.527	0.002	2.865
Std. of precipitation, 1991-1995	1000 mm	68918	0.091	0.082	0.002	0.402
Std. of precipitation, 1996-2000	1000 mm	68918	0.092	0.070	0.002	0.368
Std. of precipitation, 2001-2005	1000 mm	68918	0.092	0.080	0.004	0.788
Temperature, 1991-1995	degree Celsius	68918	8.027	7.470	-16.440	24.820
Temperature, 1996-2000	degree Celsius	68918	8.412	7.498	-15.780	25.040
Temperature, 2001-2005	degree Celsius	68918	9.225	6.826	-4.696	26.295
Std. of temperature, 1991-1995	degree Celsius	68918	0.383	0.095	0.084	0.820
Std. of temperature, 1996-2000	degree Celsius	68918	0.561	0.120	0.239	1.144
Std. of temperature, 2001-2005	degree Celsius	68918	0.252	0.127	0.004	2.576
county level						
Urban GDP per hectare, 1989	million CNY/ha.	2034	0.056	0.149	0.001	4.387
Urban GDP per hectare, 1996	million CNY/ha.	2034	0.123	0.298	0.001	8.681
Urban GDP per hectare, 2000	million CNY/ha.	2034	0.186	0.381	0.003	6.853
Agricultural GDP per hectare, 1989	million CNY/ha.	2034	0.012	0.119	0.000	5.325
Agricultural GDP per hectare, 1996	million CNY/ha.	2034	0.015	0.034	0.000	0.659
Agricultural GDP per hectare, 2000	million CNY/ha.	2034	0.018	0.043	0.000	0.977
Urban GDP per capita, 1989	10,000 CNY	2034	0.887	0.696	0.050	6.090
Urban GDP per capita 1996	10,000 CNY	2034	1.531	1.333	0.024	13.377
Urban GDP per capita, 2000	10,000 CNY	2034	2.216	1.906	0.041	19.606
Rural GDP percapita, 1989	10,000 CNY	2034	0.115	0.194	0.004	6.379
Rural GDP per capita, 1996	10,000 CNY	2034	0.156	0.120	0.010	1.722
Rural GDP per capita, 2000	10,000 CNY	2034	0.187	0.146	0.007	2.378
Road density, 1988	m/ha.	2034	0.751	1.656	0.000	41.877
Road density, 1995	m/ha.	2034	0.866	1.794	0.000	42.901
Road density, 2000	m/ha.	2034	1.043	2.136	0.000	47.960
Agricultural investment, 1994	million CNY	2034	0.075	0.387	0.000	11.783
Agricultural investment, 1995-1999	million CNY	2034	0.076	0.417	0.000	13.354
Agricultural investment, 2000	million CNY	2034	0.095	0.527	0.000	17.057

Table 4. Estimated Spatial Autoregressive Parameters

Time period	To Farm	To Forest	To Grass	To Water	To Urban
1988-1995	0.139***	0.170***	0.128***	0.206***	0.037*
	(0.006)	(0.004)	(0.007)	(0.031)	(0.022)
1995-2000	0.128***	0.109***	0.105***	0.091***	0.011
	(0.005)	(0.004)	(0.007)	(0.030)	(0.018)
2000-2005	0.116***	0.113***	0.079***	0.085***	0.063***
	(0.005)	(0.004)	(0.006)	(0.022)	(0.013)

Note: * and *** indicate statistical significance at the 10 and 1% levels, respectively.

Table 5. Prediction Accuracy and Predictive Power Assessment by Time Period and Land Use Category

Time period	Type	Farm	Forest	Grass	Water	Urban	Unused	Total
1988-1995	Hit rate by actual use	0.915	0.928	0.859	0.844	0.736	0.927	0.904
	Hit rate by predicted use	0.891	0.931	0.877	0.868	0.676	0.927	0.904
	Weighted mean of probabilities†	0.677	0.767	0.716	0.570	0.306	0.852	n.a
		(0.336)	(0.320)	(0.347)	(0.426)	(0.311)	(0.273)	n.a
1995-2000	Hit rate by actual use	0.907	0.931	0.868	0.825	0.793	0.909	0.902
	Hit rate by predicted use	0.902	0.934	0.858	0.877	0.648	0.927	0.902
	Weighted mean of probabilities†	0.680	0.766	0.690	0.586	0.344	0.863	n.a
		(0.334)	(0.318)	(0.334)	(0.416)	(0.335)	(0.276)	n.a
2000-2005	Hit rate by actual use	0.931	0.935	0.910	0.798	0.740	0.926	0.922
	Hit rate by predicted use	0.920	0.947	0.888	0.844	0.709	0.946	0.922
	Weighted ean of probabilities†	0.688	0.750	0.699	0.553	0.343	0.888	n.a
		(0.342)	(0.314)	(0.347)	(0.416)	(0.337)	(0.271)	n.a

† Weighted by the proportion of initial land use in each conversion period.

Table 6. Marginal Effects on the Probabilities of Farmland Conversion, 2000–2005

Indep. Variable	To Farm	To Forest	To Grass	To Water	To Urban	To Unused
Land quality	0.035	0.002	-0.072***	0.064***	0.013	-0.042***
	(0.033)	(0.018)	(0.019)	(0.017)	(0.019)	(0.012)
Terrain slope	0.324***	0.088***	0.028*	-0.067***	-0.363***	-0.011***
	(0.117)	(0.017)	(0.016)	(0.017)	(0.133)	(0.003)
Elevation	-1.588***	0.434***	1.749***	0.778***	-1.407***	0.033***
	(0.283)	(0.084)	(0.087)	(0.083)	(0.311)	(0.013)
Precipitation	-3.641***	2.616***	-1.231***	1.004***	1.534***	-0.282***
	(0.407)	(0.206)	(0.179)	(0.220)	(0.354)	(0.079)
Temperature	0.185***	-0.308***	0.015	0.021	0.085**	0.002
	(0.040)	(0.016)	(0.014)	(0.018)	(0.040)	(0.002)
Std Err of precipitation	2.782**	-3.150***	-2.741***	1.293	1.664	0.152
	(1.309)	(0.623)	(0.857)	(0.801)	(1.251)	(0.420)
Std Err of temperature	0.114	-2.465***	-3.324***	-0.637	6.769***	-0.458***
	(1.203)	(0.479)	(0.514)	(0.623)	(1.374)	(0.138)
Road density	0.604***	-0.678***	0.054	-0.077	0.141***	-0.044***
	(0.095)	(0.057)	(0.051)	(0.071)	(0.030)	(0.018)
Agricultural investment	0.528**	-0.415***	-0.303***	0.076	0.102*	0.013
	(0.234)	(0.126)	(0.120)	(0.195)	(0.058)	(0.019)
Urban GDP per hectare	-2.208***	1.044***	0.620**	-0.427**	0.708***	0.264***
	(0.520)	(0.245)	(0.256)	(0.179)	(0.219)	(0.097)
Agricultural GDP per hectare	-9.129	2.531	-0.905	-0.145	7.951	-0.303
	(16.776)	(7.497)	(6.089)	(1.951)	(5.977)	(0.282)
Urban GDP per capita	-0.133**	-0.149***	0.051	0.083***	0.176***	-0.027***
	(0.056)	(0.032)	(0.040)	(0.030)	(0.025)	(0.009)
Rural GDP per capita	-2.922***	-0.905**	1.623***	1.949***	0.263	-0.009
	(1.109)	(0.446)	(0.376)	(0.348)	(1.132)	(0.027)

Note: (1) Marginal effects are evaluated at the weighted sample means; the weighted means are calculated by weighting all values of variables using the proportions of land use in 2000. (2) The standard errors are estimated using delta method; *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. (3) The magnitude of marginal effects is enlarged by 100 times.

Table 7. Marginal Effects on the Probabilities of Forests Conversion, 2000–2005

Indep. Variable	To Farm	To Forest	To Grass	To Water	To Urban	To Unused
Land quality	0.051**	0.687***	-0.033	0.010***	0.001	-0.716***
	(0.021)	(0.216)	(0.022)	(0.003)	(0.001)	(0.251)
Terrain slope	-0.035***	0.310***	-0.024***	-0.010***	-0.008***	-0.233***
	(0.012)	(0.061)	(0.008)	(0.003)	(0.003)	(0.060)
Elevation	-0.603***	-1.177***	1.443***	0.084***	-0.033***	0.286*
	(0.080)	(0.143)	(0.054)	(0.017)	(0.010)	(0.155)
Precipitation	-1.909***	10.635***	-2.853***	0.077***	0.010	-5.961***
	(0.175)	(1.637)	(0.153)	(0.029)	(0.008)	(1.489)
Temperature	0.249***	-0.676***	0.235***	0.010***	0.004***	0.178***
	(0.015)	(0.040)	(0.013)	(0.003)	(0.001)	(0.071)
Std Err of precipitation	2.644***	-6.413	-0.706	0.241**	0.061**	4.174
	(0.788)	(6.005)	(0.659)	(0.113)	(0.031)	(7.531)
Std Err of temperature	2.631***	4.822***	-1.167***	0.001	0.161***	-6.448***
	(0.474)	(1.708)	(0.305)	(0.081)	(0.048)	(1.768)
Road density	0.612***	-0.792***	0.584***	0.008	0.009***	-0.421*
	(0.054)	(0.245)	(0.056)	(0.010)	(0.002)	(0.234)
Agricultural investment	0.364***	-0.791*	-0.027	0.020	0.006**	0.428
	(0.110)	(0.417)	(0.124)	(0.026)	(0.002)	(0.352)
Urban GDP per hectare	-1.286***	-2.205	-0.370**	-0.090***	0.000	3.951***
	(0.281)	(1.493)	(0.173)	(0.029)	(0.006)	(1.396)
Agricultural GDP per hectare	-2.221	10.842	-2.414**	-0.067	0.134	-6.275***
	(7.600)	(6.908)	(1.023)	(0.157)	(0.138)	(1.993)
Urban GDP per capita	0.131***	0.058	0.186***	0.015***	0.005***	-0.395***
	(0.032)	(0.155)	(0.036)	(0.005)	(0.001)	(0.130)
Rural GDP per capita	0.386	-3.197***	2.316***	0.268***	0.012	0.215
	(0.424)	(0.461)	(0.130)	(0.063)	(0.025)	(0.345)

Note: (1) Marginal effects are evaluated at the weighted sample means; the weighted means are calculated by weighting all values of variables using the proportions of land use in 2000. (2) The standard errors are estimated using delta method; *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. (3) The magnitude of marginal effects is enlarged by 100 times.

Table 8. Marginal Effects on the Probabilities of Grassland Conversion, 2000–2005

Indep. Variable	To Farm	To Forest	To Grass	To Water	To Urban	To Unused
Land quality	0.087***	0.150***	0.661***	0.064***	0.006**	-0.968***
	(0.020)	(0.035)	(0.210)	(0.014)	(0.002)	(0.239)
Terrain slope	0.008	0.077***	0.281***	-0.047***	-0.022**	-0.298***
	(0.010)	(0.011)	(0.030)	(0.011)	(0.010)	(0.034)
Elevation	-1.228***	-1.548***	3.441***	0.229***	-0.146***	-0.747***
	(0.057)	(0.059)	(0.184)	(0.052)	(0.035)	(0.121)
Precipitation	0.747***	4.289***	-0.135	0.905***	0.141***	-5.947***
	(0.152)	(0.231)	(0.929)	(0.168)	(0.045)	(0.831)
Temperature	0.009	-0.317***	0.240***	0.014	0.005*	0.050
	(0.011)	(0.013)	(0.040)	(0.013)	(0.003)	(0.048)
Std Err of precipitation	1.767**	-0.414	-8.992	1.280**	0.188*	6.170
	(0.873)	(1.323)	(7.627)	(0.620)	(0.114)	(9.824)
Std Err of temperature	2.636***	2.017***	2.662***	0.241	0.542***	-8.098***
	(0.394)	(0.417)	(0.815)	(0.431)	(0.158)	(1.131)
Road density	0.068	-0.631***	1.662***	-0.042	0.010***	-1.068***
	(0.042)	(0.084)	(0.191)	(0.051)	(0.004)	(0.268)
Agricultural investment	0.214***	-0.100	-0.825*	0.099	0.016**	0.596
	(0.087)	(0.155)	(0.463)	(0.134)	(0.008)	(0.467)
Urban GDP per hectare	-0.786***	-0.103	-4.476***	-0.459***	0.004	5.820***
	(0.236)	(0.263)	(1.432)	(0.146)	(0.020)	(1.650)
Agricultural GDP per hectare	0.333	3.938***	1.822	0.098	0.508	-6.700***
	(5.126)	(1.109)	(4.655)	(0.808)	(0.433)	(1.378)
Urban GDP per capita	-0.006	-0.153***	0.797***	0.055***	0.010***	-0.703***
	(0.031)	(0.049)	(0.121)	(0.022)	(0.004)	(0.131)
Rural GDP per capita	-1.149***	-2.681***	4.447***	1.048***	-0.041	-1.625***
	(0.293)	(0.143)	(0.502)	(0.280)	(0.072)	(0.431)

Note: (1) Marginal effects are evaluated at the weighted sample means; the weighted means are calculated by weighting all values of variables using the proportions of land use in 2000. (2) The standard errors are estimated using delta method; *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. (3) The magnitude of marginal effects is enlarged by 100 times.

Table 9. Description of Simulation Scenarios

Scenario	Description
Baseline	All variables at the observed values
No change in urban land value	Fix urban GDP per hectare at 1989 values
No change in agricultural land value	Fix agricultural GDP per hectare at 1989 values
No change in urban income	Fix urban GDP per capita at 1989 values
No change in rural income	Fix rural GDP per capita at 1989 values
No change in road density	Fix road density at 1989 values
No agricultural investment	Restrict agricultural investments to be zero

Table 10. Relative Importance of Alternative Drivers of Land Use Changes, 1988–2005

	Farm		Forest		Grass		Water		Urban		Unused	
Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Baseline	2.0	0%	-4.8	0%	-11.1	0%	0.4	0%	3.6	0%	10.0	0%
No change in urban land value	3.6	81%	-5.0	-2%	-9.9	11%	0.8	74%	3.2	-11%	7.3	-27%
No change in agricultural land value	2.1	2%	-5.0	-3%	-11.9	-7%	0.4	-3%	4.2	17%	10.2	2%
No change in urban income	0.9	-54%	-4.4	10%	-14.9	-34%	-0.2	-142%	3.0	-17%	15.6	57%
No change in rural income	3.8	87%	-5.3	-10%	-13.1	-18%	0.8	77%	4.1	14%	9.9	-1%
No change in road density	1.3	-34%	-4.0	18%	-12.0	-8%	0.5	9%	3.5	-3%	10.8	8%
No public agricultural investment	1.8	-11%	-4.5	7%	-10.0	10%	0.4	-17%	3.4	-4%	9.0	-10%

Note: The odd columns report the simulated land use changes (million hectares); the even columns report the difference between counterfactual and baseline acreage change, divided by the absolute value of baseline acreage change. A positive percentage change indicates that the increase is larger or the decrease is smaller compared to the baseline. A negative percentage change indicates the opposite.

Rice Crop Monitoring using Multitemporal Data

Mrs. Hong Anh
Remote Sensing and GIS centre, NIAPP, Vietnam
honganhngt@gmail.com

1. BACK GROUND

Rice is the major crop in Vietnam. An effective rice monitoring program is necessary at regional and national level to control and maintain a close balance between rice production and food demands,
Estimate of rice production at present based on ground survey, which is time and manpower consuming,
A large part of rice growth period coincides with rainy season, thus limiting the number of cloud free optical data,

2. OBJECTIVES

Rice distribution mapping to address land management and related agricultural issues: irrigation, subsidies policy..
Rice cropping mapping: single crop, double crop, triple crop..
Interannual change in rice cropping system
Rice monitoring to monitor crop status all along the crop seasons, as key inputs for production management.

3. STUDY AREA

The Red River Delta (Vietnamese: Đồng Bằng Sông Hồng) is the flat plain formed by the Red River and its distributaries joining in the Thai Binh River in northern Vietnam. The delta measuring some 15,000 square km is well protected by a network of dikes. It is an agriculturally rich area and densely populated. Most of the land is devoted to rice cultivation.
The centre of the Red River Delta is very flat, mostly located in the height of 0.4 – 12m above sea level in which 56% is lower than 2m.
The Red River Delta includes 11 provinces and cities: Hanoi, Hải Phòng, Hà Tây, Hải Dương, Hưng Yên, Bắc Ninh, Vĩnh Phúc, Thái Bình, Hà Nam, Nam Định, Ninh Bình.
Thái Bình is a coastal eastern province in the Red River Delta region in Vietnam. Covering an area of 1,542.24 km2, Thai Binh makes up 0.5 percent of total area of Vietnam. The province borders on the Gulf of Tonkin in the east, Nam Dinh and Ha Nam provinces in the west and southwest and Hai Duong, Hung Yen and Hai Phong City in the north.
Locating on the edge of the tropical climatic zone, Thai Binh has annual average temperature of 23 - 24^0C, average rainfall of between 1,400 mm and 1,800 mm and humidity of about 85-90 percent. From May to the end of October, it is always rainy and hot while the weather from November to April next year is dry.
Having good conditions in land, climate and topography, Thai Binh, a key paddy production province in the Red River Delta has over the past few years continued to maintain strong growth in rice production yielding 14-15 tons/ha with a constant improvement in output, yield and quality. Due to humid and tropical climate with a temperature ranging at 22-23C0, two paddy crops are planted in a year: the Spring lasting from January 25 to June 20 and the Mua lasting from 20 June to December 30.

3.1 Used Data

MODIS data

MODIS imagery is acquired with 36 spectral bands in visible, near infrared, short wave and thermal ranges (from 0,46 µm to 14,4 µm) and spatial resolution from 250m (band 1 and 2), 500m (band 3-7) and 1000m (for remaining bands). The repeat period of MODIS is high that makes it possible to capture 4 images daily (2 for day time and 2 night scenes). The large image covering area (2230x2230km), high temporal resolution and multi-spectral bands, especially sensitive with atmosphere have provided good opportunities for research works in cloudy, tropical region using MODIS imagery.
In this study, the 8-day reflectant composite AQUA MODIS data level 3 from LP DAAC, acquired in 2010 are utilized. Each scene includes 2 bands (band 1 – red band, 645nm, band 2 – near infrared, 845nm), 250m spatial resolution in global Sinusoidal projection.
The pre-processing works have been implemented to customize this data set with local conditions in Vietnam, including georeferencing, image crop, and cloud removal.

ENVISAT ASAR APP

This study used the ENVISAT ASAR APP data of HH and VV polarization, IS2 incidence angle (19.2o – 26.7o) at 35-day repeat interval. The APP images have a nominal spatial resolution of 30m x 30m and pixel size of 12.5m x 12.5m, with a swath width of about 100km. The data under study have been acquired at 11 dates in 2008 covering three rice crops (Table 1).
For rice mapping, data should be exactly at the same geometry (same track-incidence angle IS2, ascending or descending). It was decided that only the data listed in table 1 can be used for the AGRIM pilot.

AUXILIARY DATA:

Topographic map at 1/25000 provided by MONRE
Land use map of Thai Binh completed in 2005 is provided by MONRE, at the 1/50,000 scale. The land is classified into: paddy rice (rice, mixed rice and other annual crops), annual crops, acquaculture, water bodies, residential areas and others.
Weekly agriculture production statistics of Thai Binh agriculture department.

3.2 Using MODIS image for land cover mapping

NDVI & RVI indices

Normalized Difference Vegetation Index (NDVI) has been broadly used in mapping vegetation coverage, monitoring vegetation growth, crop disease and drought detection, acrage, yield and product estimation.

$$NDVI = (NIR-R)/(NIR+R)$$

In which: NIR - near infrared; R - Red

Ratio Vegetion Index (RVI) mostly used for leaf area index, dry biomass, and leaf clorophyl ratio determination. Its common applications are vegetation coverage ratio and vegetation classification.

$$RVI=NIR/R$$

The values of NDVI and RVI are calculated for each 8-day composite MODIS scene. The series data of those indices are then compiled to create multi-temporal data sets. The multi-temporal NDVI set is used to create annual vegetation coverage and vegetation change maps. The study on vegetation indices (NDVI and RVI) has come up into a conclusion that monitoring the changes (by crop season) of different vegetation types can be determined by observing the multi-temporal graphs of vegetation indices.

Table 1. List of ENVISAT ASAR data used

Rice Crop	**Observation date**	
	Ascending pass	Descending pass
Spring		April 14 *
	May 11	May 19
	June 15	June 23
Mùa	July 20	
	August 24	September 01
	September 28	
		October 06
	November 02	

Among the three vegetation indices, NDVI shows the most significant separation of vegetation types and therefore, being applied for mapping land cover/land use of the Red River delta (RRD). The land use classification of RRD includes 9 classess: (1) Rice cultivation (double-crop); (2) Rice-crop mixture (double-rice and single crop, or single rice and 2-3 crops); (3) Rice-fish cultivation; (4) Crops (annual crops); (5) Perennial crops; (6) Forest land; (7) Settlement and exclusive land use; (8) Water bodies (natural or aquaculture); and (9) Unsued land.

The possibility of applying RVI for land coverage mapping and land cover classification is quite low. In general, the characteristics of monthly spectral graph lines (derived from MODIS data) are likely distinced for 9 land use classess. They are used as basics for land use/land cover classification in the RRD, as well as for evaluation of efficiency in terms of classification for each vegetation index.

Land cover mapping

The monthly NDVI data set in 2010 (12 bands) is processed by an image processing software ENVI 4.7. The accurary assessment is done by comparing the classification results with reliable information from the latest high-scale land use maps (1/50.000) and field survey data. Kappa and Overall Accuracy (OA) indices are determined within 72 samples, resulted in Kappa = 0.8798 and OA = 89.6%.

3.3 Using ENVISAT ASAR APP data for rice crop mapping

Processing of ASAR APP data using BEST v.4.0.5, that is used to generate backscattering images, to co-register them and to export them to the BIL format which are input to the next step.

Image calibration consisted of correcting SAR images for incidence angle effect and for replica pulse power variations, to derive physical values. This transformed SAR precision images into intensity images expressed in σ^o in dB (decibel). Image registration was performed to register the calibrated images (dual polarizations and multi-date) using correlation method.

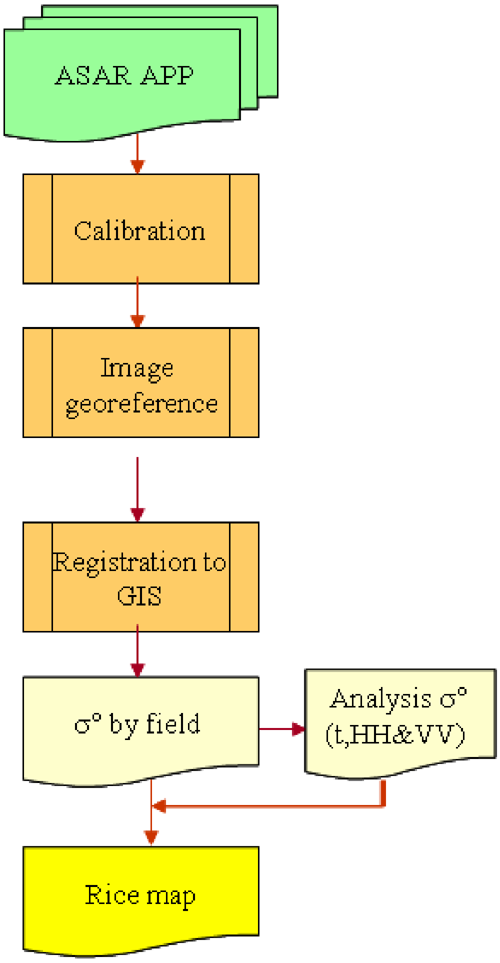
Statistical Analysis

The rice mapping methodology will be derived from the results of backscattering analysis carried out at the Dong Hung district of Thai Binh province. An ASAR APP time series images are processed and analysed regarding the HH/VV ratio of rice and non-rice classes in order to retrieve information relevant to paddy rice monitoring. The result will be applied to generate rice map for the whole Thai Binh.

A statistical study is performed on the “rice” and “non-rice” pixels. Figure 4 presents the ratio of the mean HH and VV values (<HH>/<VV>) for these 2 classes at the 11 dates. (Conversion to dB is done only after averaging and ratioing). The <HH>/<VV> of non-rice class exhibits values around 1.79 dB at all date, whereas the rice class shows variations as a function of growth stages during each crop season with maximum values of 4.5 and 5 dB found at the peak.

The difference in dB between the polarisation ratio of the mean intensities <HH>/<VV> of these classes indicates a high class separability (difference > 2 dB) at 2 dates per season. Thus mapping rice with a threshold on HH/VV at a single date appears possible at 4 of 11 dates.

Multi-channel Filtering



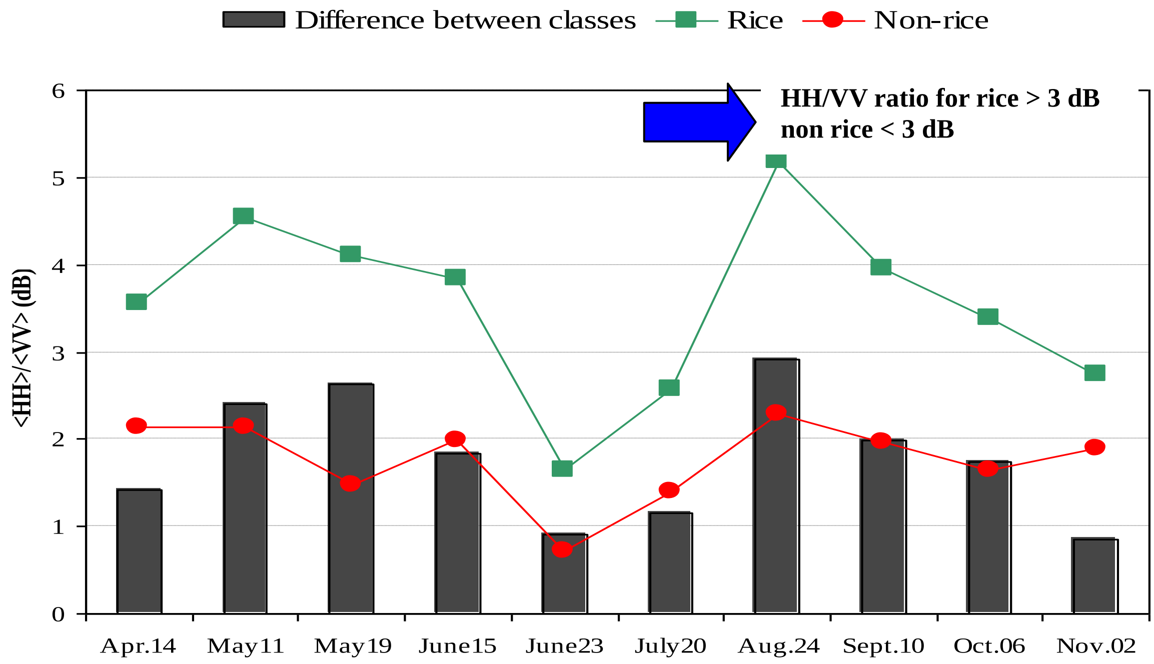


Fig. 4. Polarization ratio of mean <HH>/<VV> of "rice" pixels (green squares) and "non-rice" pixels (red circles). Grey bars show the difference of this ratio between the classes.

Before analysing the backscatter images, the speckle noise must be reduced. A multi-channel filter developed by Quegan and Yu (2001) was applied to reduce the speckle noise in SAR images and thus to increase the original number of looks in the image to a higher equivalent number of looks, without reducing the spatial resolution. The filter linearly combined M input images on a pixel-to-pixel basis with M = 22 images (11 dates and 2 polarizations), to create M output images with reduced speckle. The previous analysis results have shown that a 7x7 window is selected for the multi-channel filtering, resulting in an ENL of 21.56.

Rice/non-rice mapping

Classification method based on the temporal change of HH and VV and the ratio HH/VV which are performed for the Spring and Mua rice cycles during the year 2008 to map rice and non-rice. A threshold of HH/VV value = 3dB is used to segment rice and non-rice area. In order to reduce the confusion with other non-rice area having high HH/VV ratio (e.g. reed or marshland with vertical structure of the plants), an additional criteria were added.

The statistical analysis of rice and non-rice pixels has defined that the ratio of the mean HH and VV values during growth stages varies in 2,5 - 3,2 dB. The threshold of 3 dB of HH/VV is not conformable to detect rice fields. Hence, the temporal changes of HH or VV are valuable in those cases.

Table 2. Rice mapping criteria based on ASAR APP 2008 of Thai Binh

Rice crop	Date	(HH/VV)dB	Other
Spring	14/04/2008	>=2.6	
	11/05//2008	>=2.8	
	15/06//2008	>=2.8	
	23/06//2008		((HH/VV) $_{\text{on 15 of June}}$ dB) > 3 and (HH$_{\text{(on 5 of November)}}$ – HH $_{\text{(on 23 of June)}}$)dB <= 3)
Mua	20/07/2008		((HH/VV) $_{\text{on 24 of Aug}}$ dB) > 3 and (HH($_{\text{on 24 of Aug}}$)- (HH $_{\text{on 20 of July}}$)dB >3)
	24/08/2008	>=3	
	28/09/2008	>=3	
	06/10/2008	>=2.8	
	02/11/2008		((HH/VV)dB $_{\text{on Sept. 28}}$) > 3 and (HH$_{\text{on Sept. 28}}$- HH $_{\text{on Nov.02}}$)dB <=3)

RESULTS

Rice cultivation area evolution in 2008 of Thai Binh is summaried in the table bellow:

Crop	**Acquisition dates**	**Rice surface** *(ha)* **derived from SAR**
Spring rice: transplanted at the end of February – beginning March; harvested from the end of June to beginning July.	14/04/2008	83753.1
	11/05/2008	85112.5
	15/06/2008	74924.7
	23/06/2008	26975.8
Mùa rice: transplanted at beginning July; harvested from October to beginning November.	20/07/2008	78919.9
	24/08/2008	83952.2
	01/09/2008	83952.2
	06/10/2008	65424.7
	02/11/2008	143.8

To assess the rice maps resulted from SAR, the comparisons of rice surface measured on the maps and local weekly statistics in 2008 are conducted and turned on the accuracy of 94%.

3.4 Using ENVISAT ASAR APP data for rice crop monitoring

Ground Data acquisition

Organized a study tour in Red river delta on 09th December 2007. The objectives were to have a look about the different crops elementary areas: permanent crops, rice crops, subsidiary cropsand to have explanations about the land use changes.

Sample sites selection: August 08

Field works: Measurements on 42 rice plots: rice growth stage, density, height, water management, biomass in August 23-24, September 1, September 28, October 06, October 25

Acquistion Date		Rice Area (ha)	
Local statistic	**SAR Image**	**Local statistic**	**SAR Image**
17-Apr	14-Apr	84189.0	79326.8
15-May	11-May	84189.0	86189.2
11-Jun	15-Jun	81089.0	70982.0
25-Jun	23-Jun	29831.0	28007.7
23-Jul	20-Jul	80420.0	74025.8
20-Aug	24-Aug	83724.0	86702.6
1-Oct	28-Sep	77525.0	73115.7
8-Oct	6-Oct	66725.0	58656.7
5-Nov	2-Nov	0.0	141.5

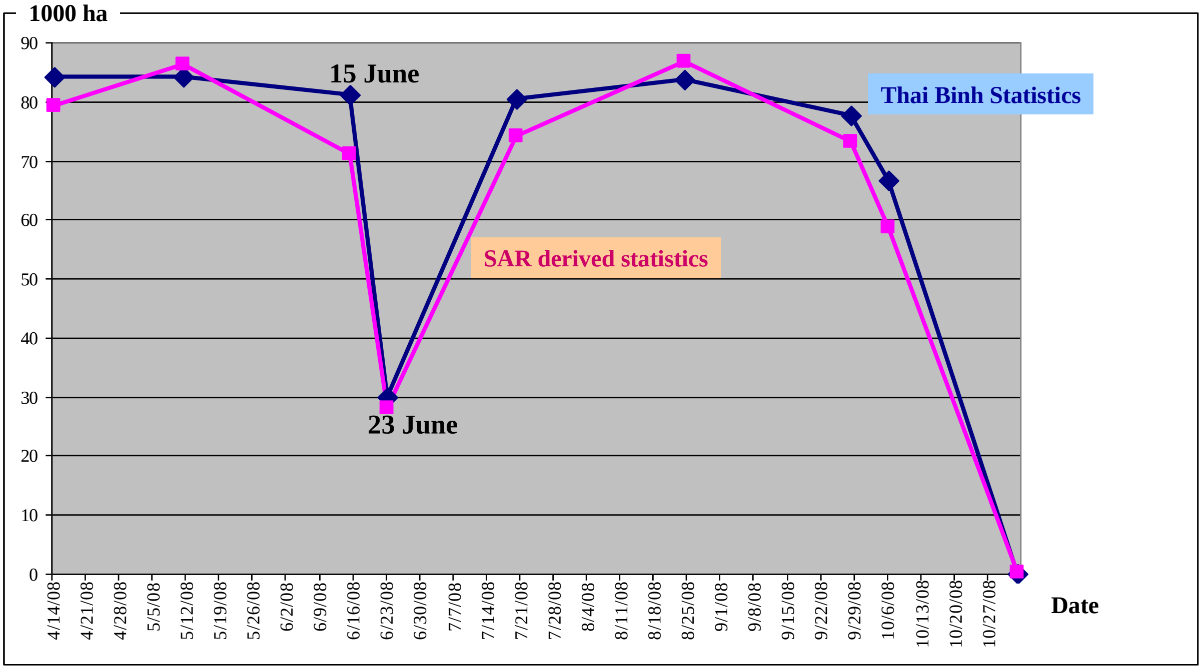


Fig 16. Assessment of areas covered by rice (ha) derived from SAR and Thai Binh statistics.

Rice growth monitoring

Analysis of field samples and ASAR images to evaluate the SAR backscatter changes in rice growth cycles, as a basis for the study of the relationship between backscatter values on ASAR image with rice parameters (plant height, fresh biomass and dry biomass) and combine the information obtained from ASAR images with rice growth models to predict rice yield.

3.5 Conclusions

With medium spatial resolution (250m), MODIS data covers a large spatial surface of the earth such as the Red River delta in Vietnam. The high frequency of repeating period in MODIS data acquisition allows monitoring status of many geographical phenomena, and observing environmental changes. The data processing, index selection and classification methodologies of this study have been inherited from previous researches worldwide that makes land use /land cover mapping result using NDVI and RVI more efficiently. Beside, the characteristics of the main crops and other features in the region have been continuously studies for many years and have become an important knowledge base, leading to high accuracy classification result of this research work.

This study proves the possibility of using MODIS data for crop monitoring and land use/land cover change observation. This is a low-cost but efficient solution and suitable for regional scale such as the Red River delta.

Application of algorithms and parameters to detect rice areas based on the change by time of HH, VV backscatter coefficient and HH/VV ratio in ASAR 2008 and 2010. The map of rice in Thai Binh province was established with an overall accuracy reached 90,2%, Kappa coefficient was 0.8 and the accuracy of rice reached 97,64%.

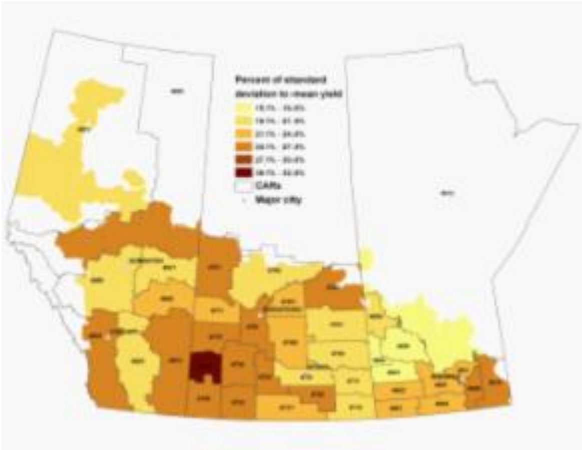
The process of rice mapping and rice yield forecasting have been established. Two models that predict yield for Spring and Mua crops for Dong Hung, Thai Binh based on multivariate regression analysis between measured rice yield and HH/VV ratio of ASAR APP. The result of predict yield of Spring and Mua crops in Dong Hung, Thai Binh reached a relatively high prediction accuracy for both crop seasons, that reached to 90%.

Remote sensing technology bring new advantages to the monitoring and forecasting crop yields.

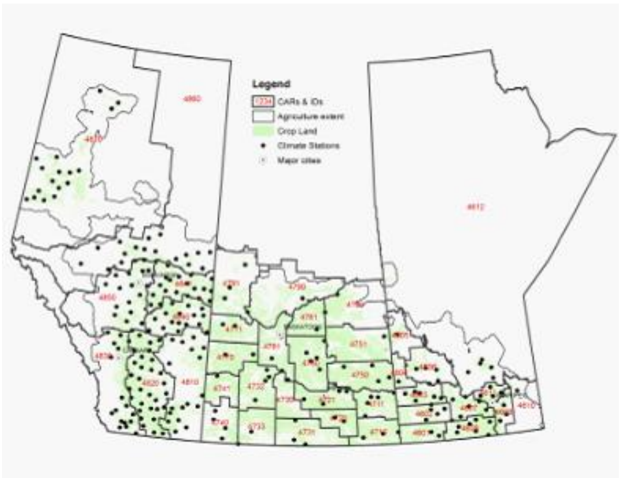
CLOUR GRAPH

Canadian Crop Yield Forecaster (CCYF)

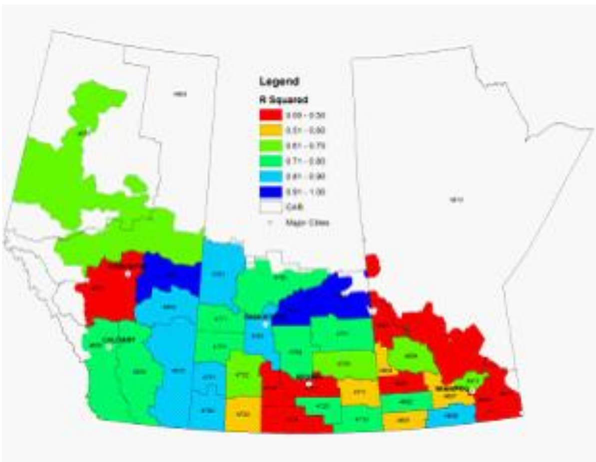
: a GIS and statistical integration of agro-climates and remote sensing information



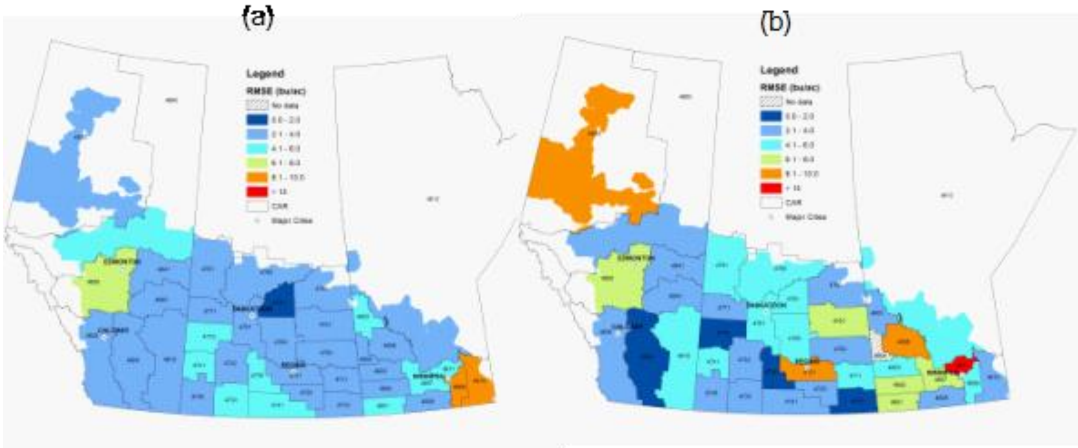
Map 1: Distribution of historical (1976-2011) spring wheat yield variation (percentage of standard deviation over the long term mean) across the 40 Census Agricultural Regions (CARs)



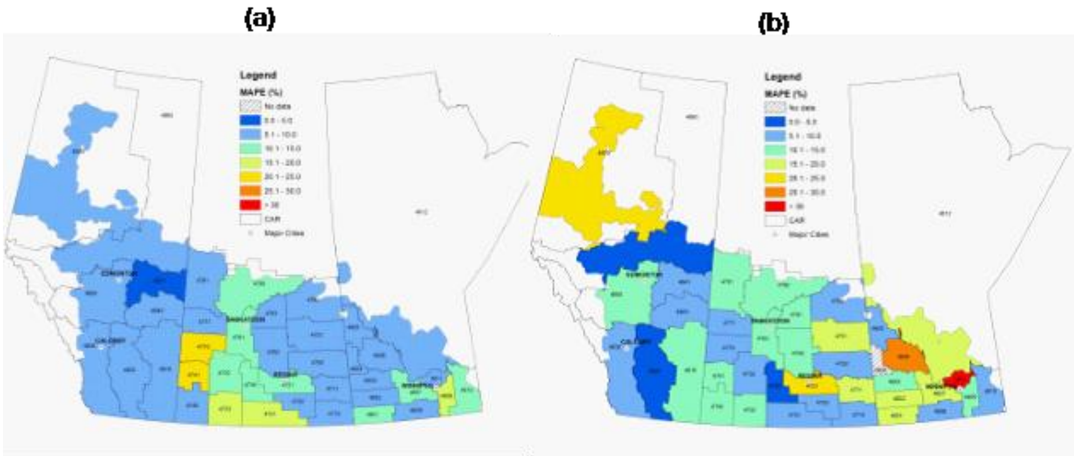
Map 2: Distribution of Crop land, agricultural extent and climate stations in the prairie CARs



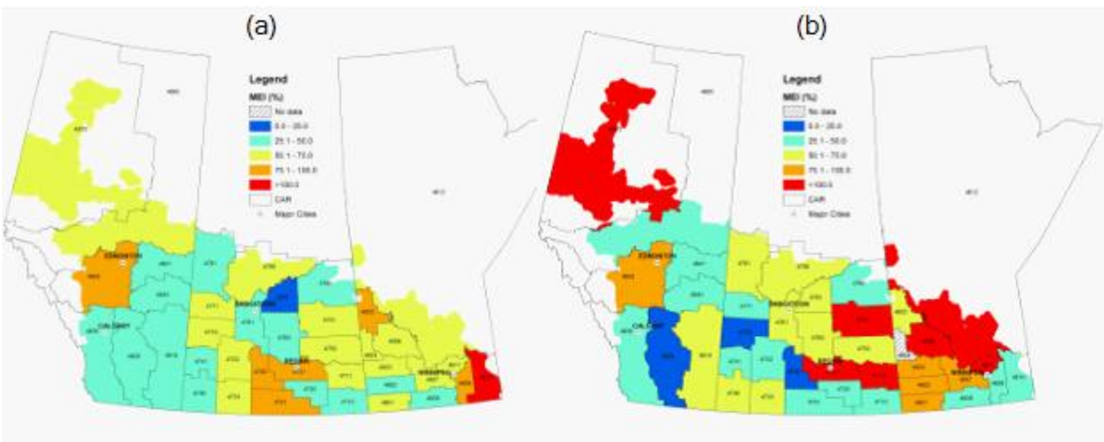
Map 3: Coefficient of determination (R^2) of the spring wheat yield forecasting model across 40 prairie CARs during the model calibration period (1987-2008).



Map 4: Root Mean Square Error (RMSE) of the forecasted spring wheat yield across 40 prairie CARs during the model calibration period
(a) and during the independent test period (b). The missing data in panel (b) are caused by the missing survey yield during the three test years (2009-2011).



Map 5: Mean Absolute Percentage Error (MAPE) of the forecasted spring wheat yield across 40 prairie CARs during the model calibration period (a) and during the independent test period (b). The missing data in panel (b) are caused by the missing survey yield during the three test years (2009-2011).



Map 6: Model Effectiveness Index (MEI) of the forecasted spring wheat yield across 40 prairie CARs during the model calibration period
(a) and during the independent test period (b). The missing data in panel (b) are caused by the missing survey yield during the three test years (2009-2011).

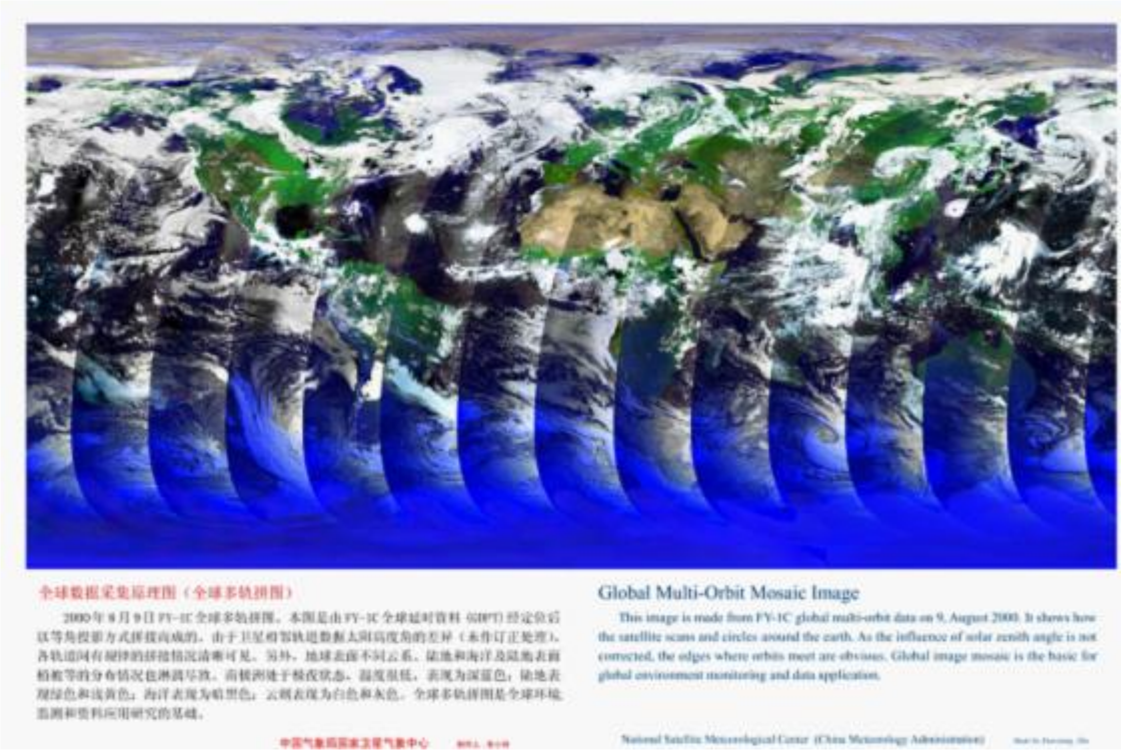


Fig. 1 the Global coverage of FengYun -1 polar orbiting satellite

Fig.2 the portal of the FengYun satellite data services

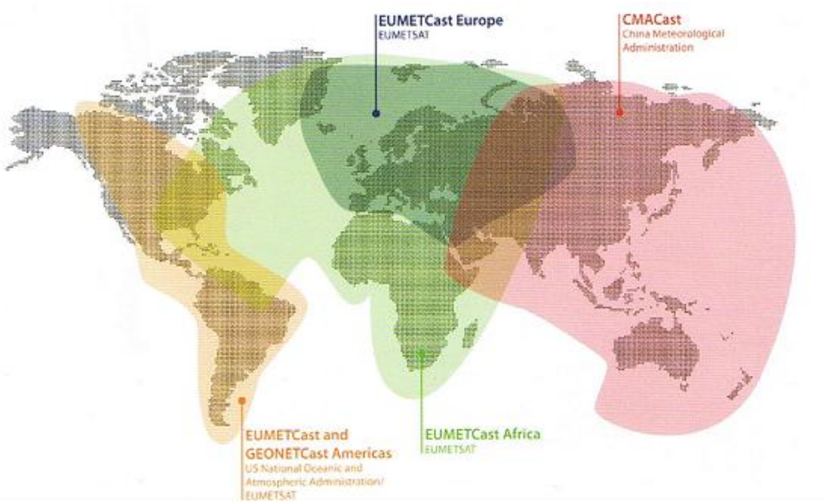


Fig.3 the footprint of the CMACast and other GEONETCast components

Fig. 4 the witness of the donation of CMACast user stations in 2007

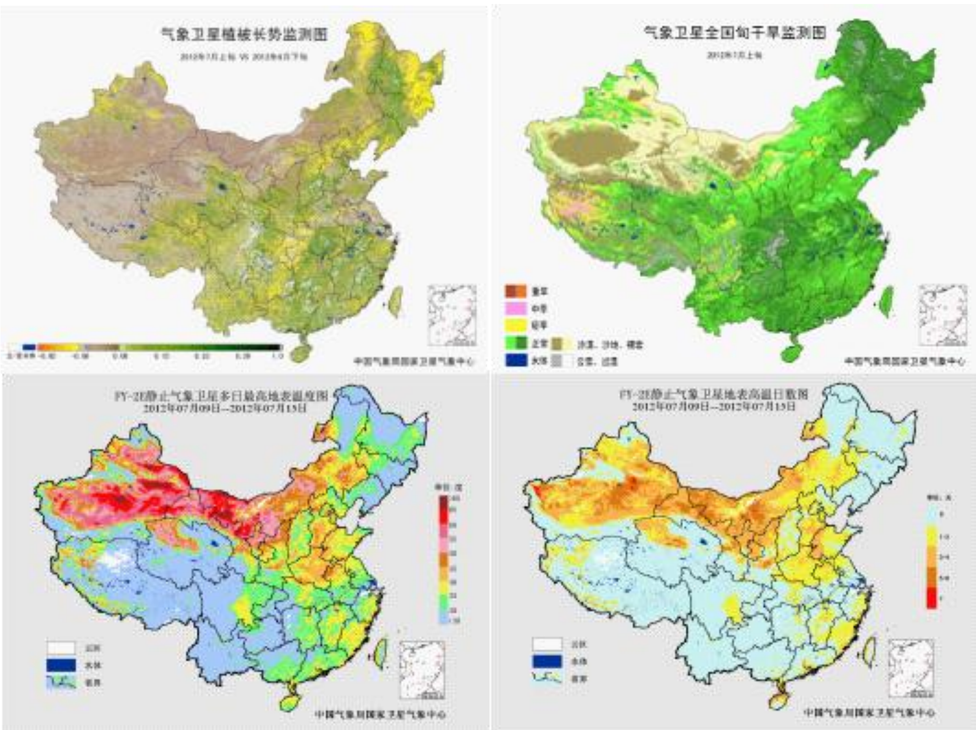
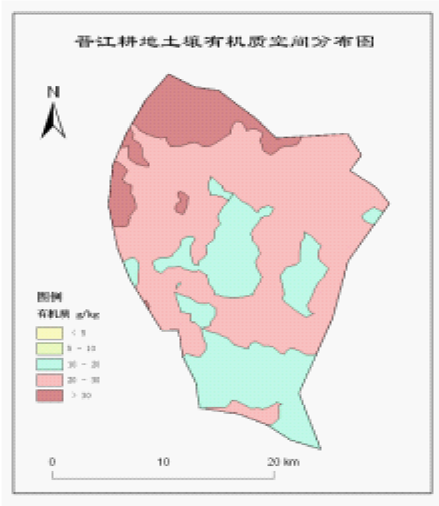
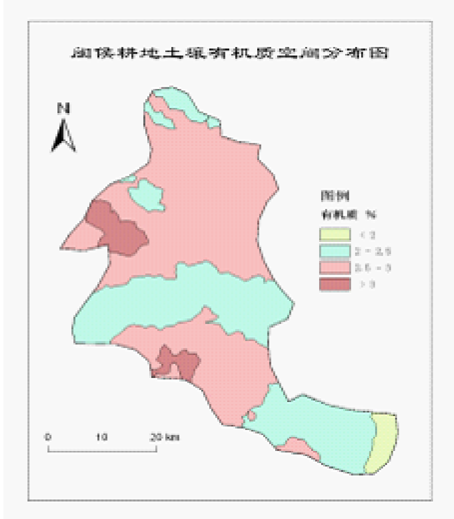
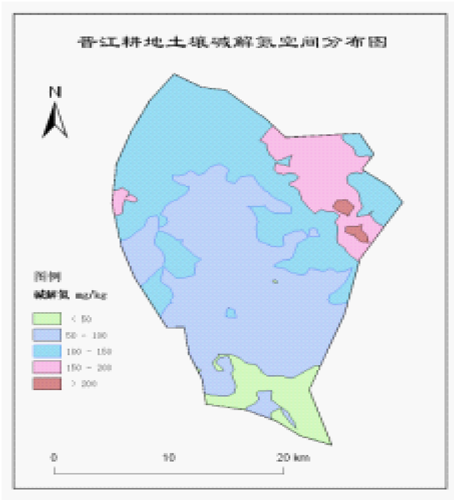
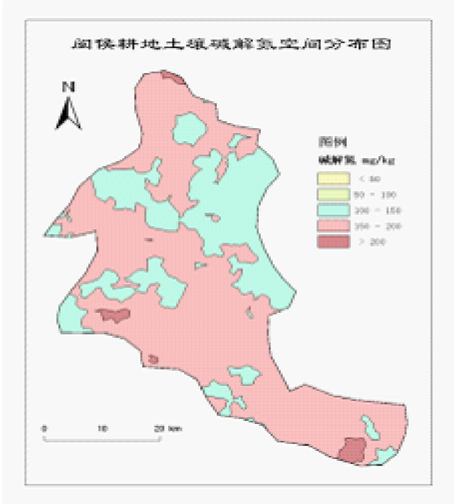


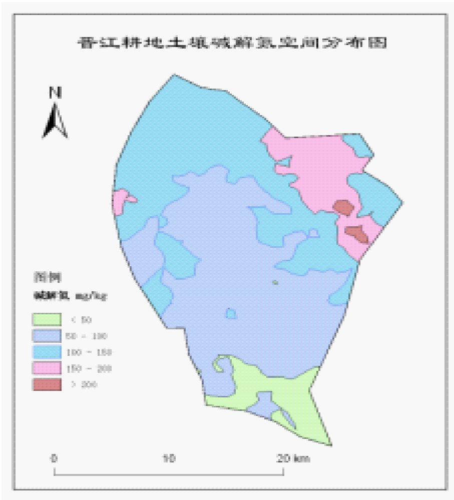
Fig. 5 the products retrieved from FY satellites

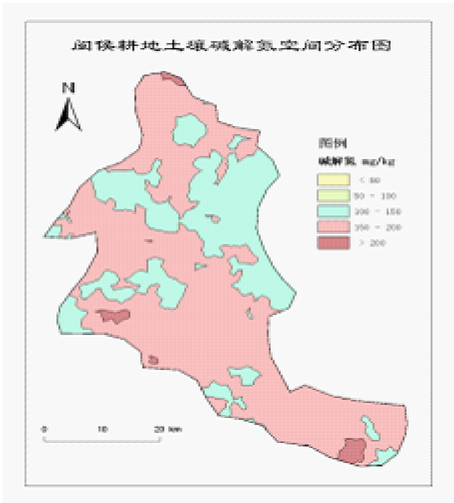

晋江耕地土壤有机质空间分布图
N
图例
有机质 g/kg
< 5
5 - 10
10 - 20
20 - 30
> 30
0
10
20 km


闽侯耕地土壤有机质空间分布图
N
图例
有机质 %
< 2
2 - 2.5
2.5 - 3
> 3
0
10
20 km


晋江耕地土壤碱解氮空间分布图
N
图例
碱解氮 mg/kg
< 50
50 - 100
100 - 150
150 - 200
> 200
0
10
20 km


闽侯耕地土壤碱解氮空间分布图
N
图例
碱解氮 mg/kg
< 50
50 - 100
100 - 150
150 - 200
> 200


晋江耕地土壤碱解氮空间分布图
N
图例
碱解氮 mg/kg
< 50
50 - 100
100 - 150
150 - 200
> 200
0
10
20 km


闽侯耕地土壤碱解氮空间分布图
N
图例
碱解氮 mg/kg
< 50
50 - 100
100 - 150
150 - 200
> 200

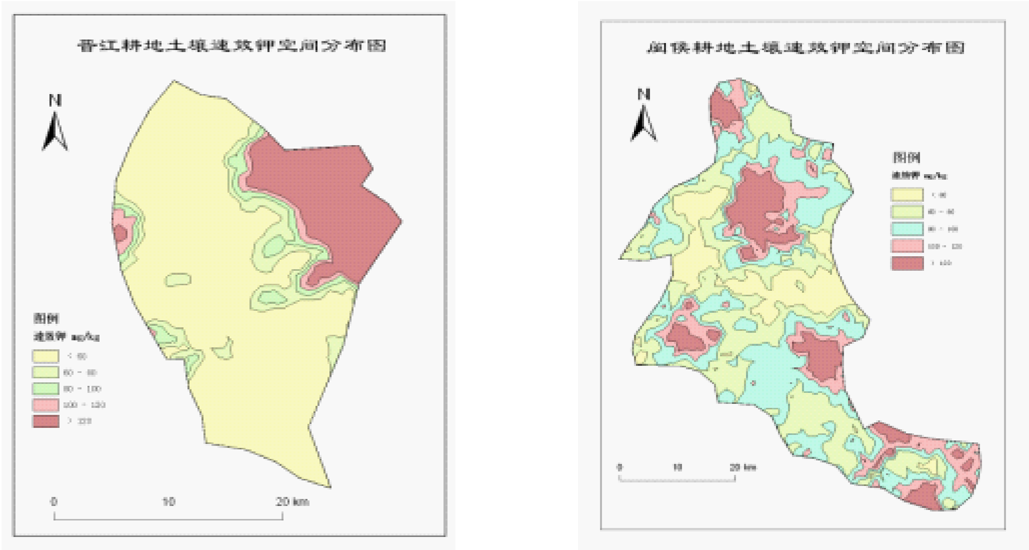


Fig 2   Spatial distribution patterns of contents of soil nutrients

An Overview of the Use of Remote Sensing and GIS for Paddy Crop Monitoring and Yield Estimation to Strengthen National Food Security in Indonesia

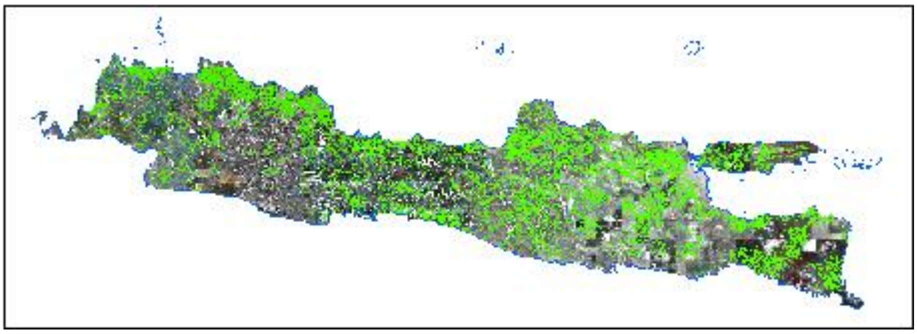


Figure 1. Map of Paddy Field of Java and Madura Island (Pusdatin, 2010)

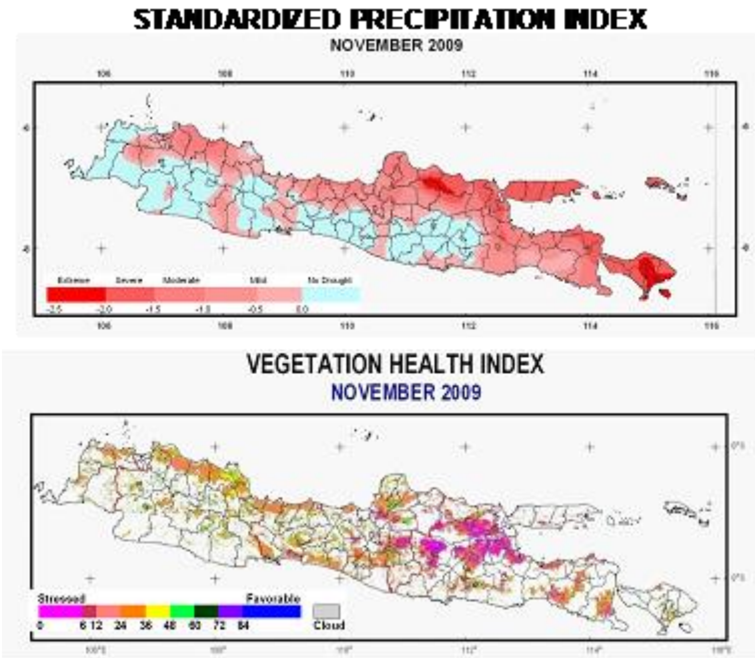


Figure 2. SPI (of TRMM) and VHI (of MODIS) analysis during El Nino of Java Island (LAPAN, 2010)

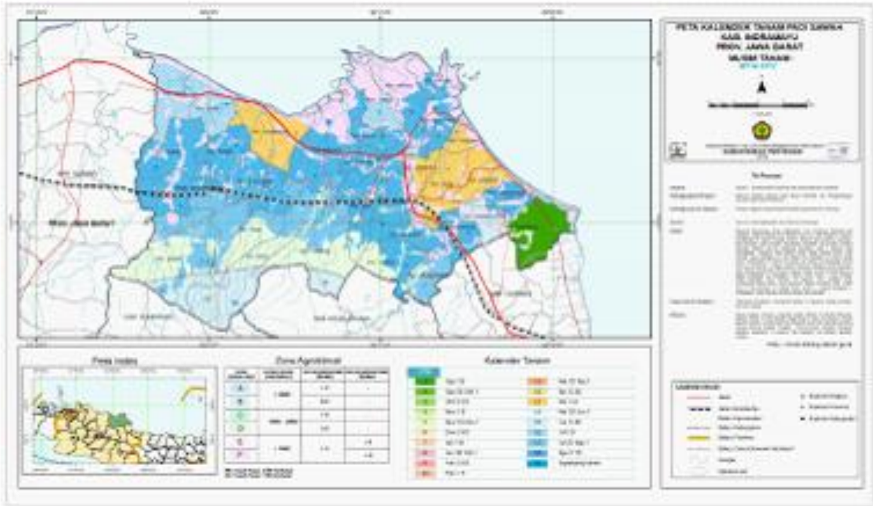


Figure 3. Integrated Cropping Calendar of Indramayu District, West Java Province (IAARD, 2012)

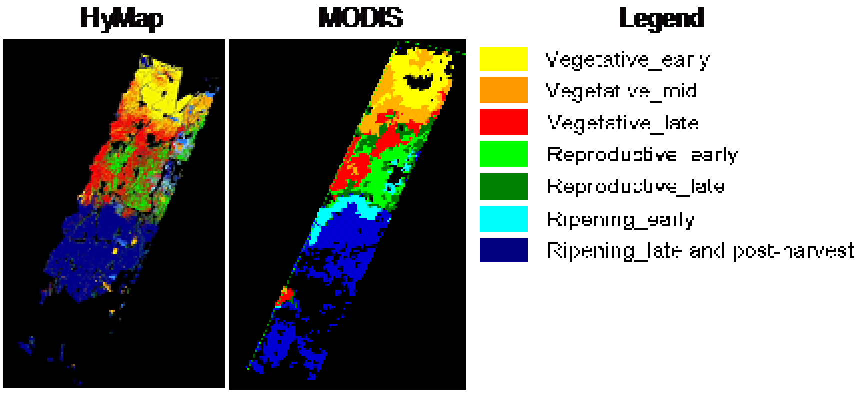


Figure 4. MODIS and hyperspectral data for paddy growing stage identification(BPPT, 2012)

Agricultural Monitoring by Earth Observation Satellite

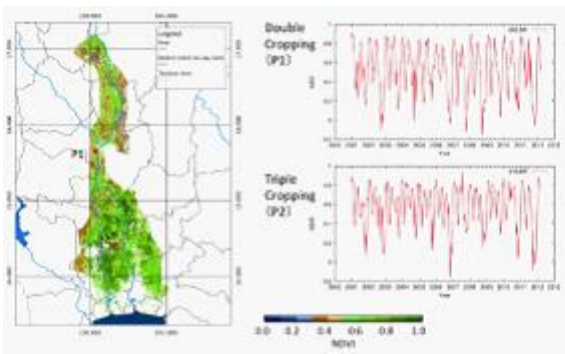


Figure 2. Difference in the crop calendars of Chao Phraya basin, Thailand .

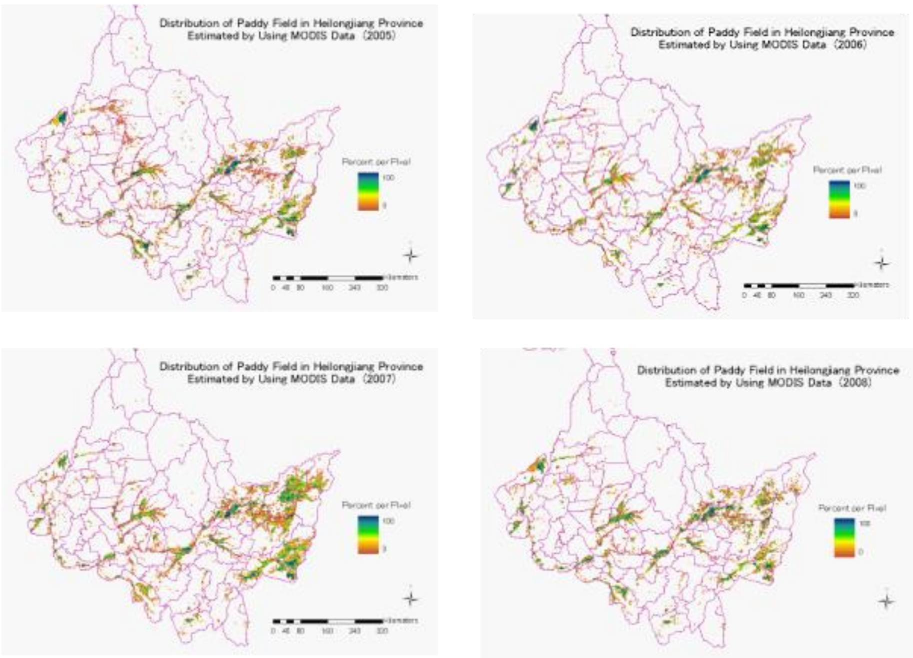


Figure 7 Estimation of distribution of paddy field of Heilongjiang Province in 2005 to 2008

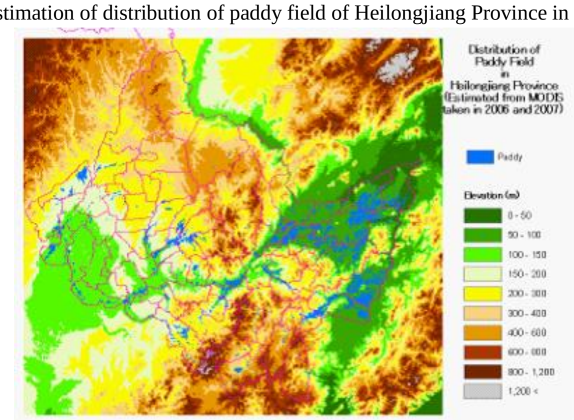


Figure 8 Distribution of paddy field overlapped on digital elevation data

Figure 12 Administrative map of Karawang District ova on LANDSAT imagery

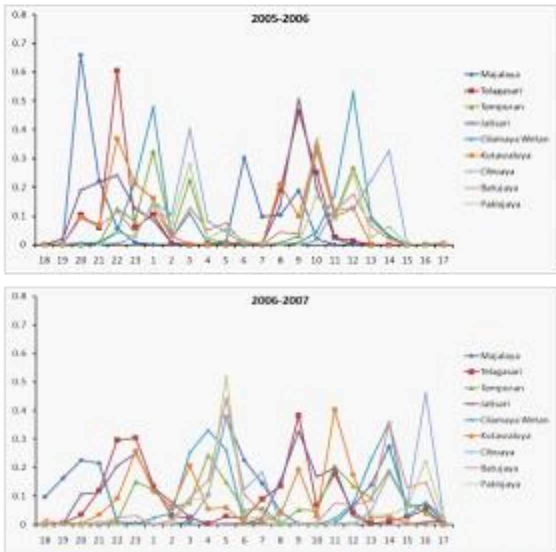


Figure 13 Temporal changes of rice planted area by Sub-Dist year of 2005 to 2006 (above) and 2006 to 2007 (below)

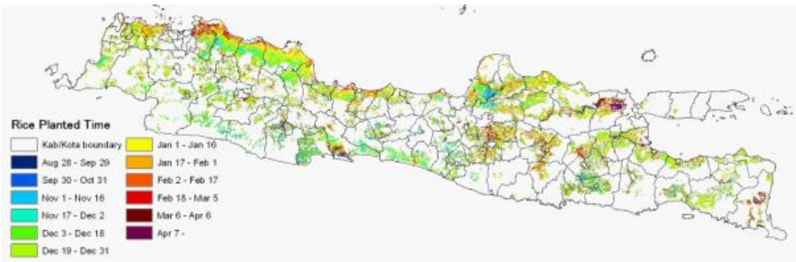


Figure 14 Distribution of first rice planted time estimated by using MODIS data

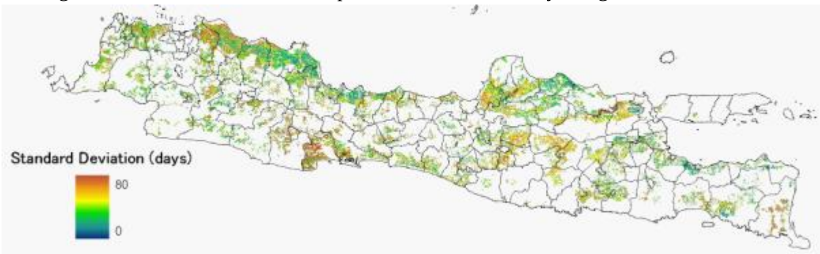


Figure 16 Yearly trend of deviation of date of rice planted time from averaged value

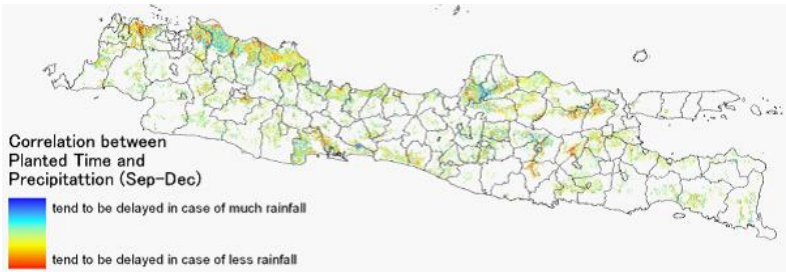


Figure 17 Correlation between first rice planted time and rainfall

Application of Remote Sensing and GIS Technology on Crops Productivity among APEC Economies : Experiences of Chinese Taipei

Fig.1. The browse and query display system of farmlands land cover database

Mapping the Rice Cropping Systems Using Time Series Satellite Data

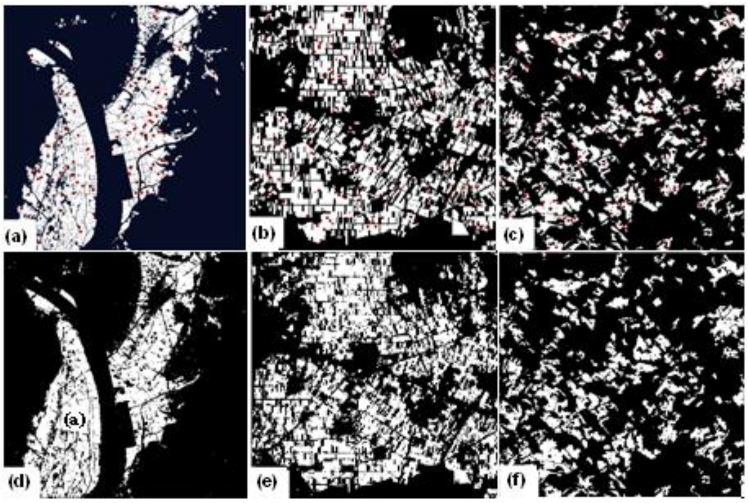


Fig. 2. The ground reference data (a, b, and c) with reference to the classification results (d, e, and f) derived from the classification of the 2005 SPOT NDVI data: (a−d) Taitung study site, (b−e) Chiayi study site, and (c−f) Taoyuan study site. The red dots presented in the ground reference maps were used to derive training patterns

Rice Crop Monitoring using Multitemporal Data

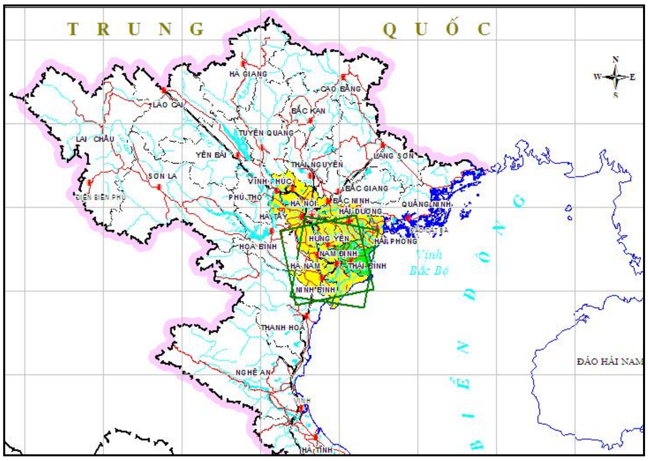


Fig. 1. The North of Vietnam: Location of the frames of ENVISAT ASAR APP scenes on the pilot area - Red River Delta

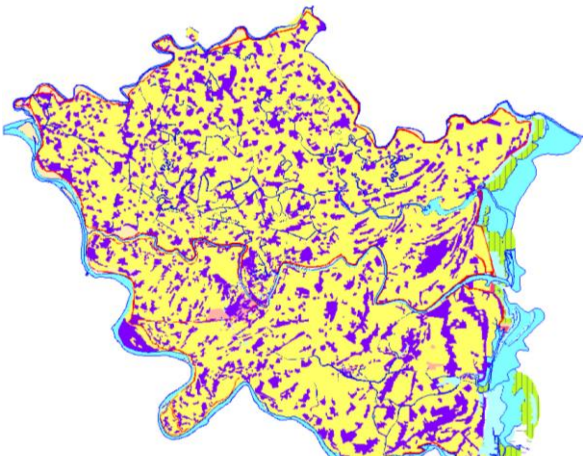


Fig. 2. Land use map 2005 of Thai Binh


The Application of Remote Sensing and GIS Technology on Crops Productivity