Sustain Sci (2010) 5:29–38
DOI 10.1007/s11625-009-0094-0

SPECIAL FEATURE: ORIGINAL ARTICLE Land use and ecosystems

Modeling changes in paddy rice sown areas in Asia

Wenbin Wu · Ryosuke Shibasaki · Peng Yang · Huajun Tang · Kenji Sugimoto

Received: 13 June 2008 / Accepted: 16 October 2009 / Published online: 9 December 2009

Abstract Paddy rice fields in Asia account for over 90% of global total rice cultivation area, and the major rice-producing countries of Asia account for over one-half of the world's population. Monitoring and understanding the dynamic changes in paddy rice agriculture in Asia are very important for agricultural sustainability, food and water security, and greenhouse gas emissions. This paper presents a crop choice decision model that dynamically simulates future changes in sown areas of paddy rice in Asia. This model was developed under the framework of Action-in-Context (AiC) with the aim of understanding land users' decisions on crop choices among a set of available alternatives using a crop utility function. Empirical validation for the model conducted after model construction indicated the reliability of the model for addressing the complexity of current agricultural land-use change and its capacity for investigating long-term scenarios in the future. Finally, the model was applied for future scenario analysis over a time frame of 30 years with 5-year increments, beginning from the year 2005. The simulation results provided insights into rates and trajectories of changes in Asian rice areas over the test period, with the resulting implications for future agricultural sustainability in Asia. These outcomes can improve understanding of projected land-use changes and explain their causes, locations and consequences, as well as providing support for land-use planning and policy making.

Keywords Paddy rice · Sown area change · Modeling · Crop choice decision

Edited by Mitsuru Osaki and Ademola Braimoh, Hokkaido University, Japan.

W. Wu (✉) · R. Shibasaki · K. Sugimoto
Center for Spatial Information Science,
University of Tokyo, Tokyo 153-8505, Japan
e-mail: wwbyn@iis.u-tokyo.ac.jp; wwb@mail.caas.net.cn

W. Wu · P. Yang · H. Tang
Institute of Agricultural Resources and Regional Planning,
Chinese Academy of Agricultural Sciences,
100081 Beijing, China

W. Wu · P. Yang · H. Tang
Key Laboratory of Resources Remote Sensing and Digital Agriculture, Ministry of Agriculture, 100081 Beijing, China

Introduction

Agriculture is essential to human survival and societal development. Agricultural sustainability has become a critical issue that is central to the sustainable development of complex human–environment systems (Pollock et al. 2008). The general goals of agricultural sustainability are to maintain a sufficiency of land for agriculture, to guarantee food security, to improve current living standards, to safeguard the development of future generations and to establish harmonious mechanisms for agriculture and economic development that ensure a prosperous rural society (Pretty 2008; Zhao et al. 2008). The primary function of agriculture is to provide food for human beings, thus the prime aim of sustainable agricultural development is to secure enough food for present and future generations.

Rice is one of the most important cereal crops in Asia. Paddy rice fields in Asia account for over 90% of the total global rice cultivation area, and the major rice-producing countries in Asia account for over one-half of the world's population. Rice is planted in flooded soil environments (irrigated and rainfed); irrigation for agriculture accounts for over 80% of the fresh water withdrawals in most Asian countries, with several of the countries reporting over 95%

of fresh water used for irrigation (Xiao et al. 2006). These high levels of irrigation raise concerns about water resource management. Furthermore, seasonally flooded rice paddies are a significant source of methane emissions (Li et al. 2005), contributing over 10% of the total methane flux to the atmosphere (IPCC 2007), which may have a substantial impact on atmospheric chemistry and climate. Therefore, monitoring and understanding the dynamic changes in paddy rice agriculture in Asia are important for agricultural and environmental sustainability, food and water security, and greenhouse gas emissions.

A number of studies have been conducted to analyze and monitor the past or present geographic distribution of Asia paddy rice and its dynamic changes over time and space, with the aid of remote sensing (Kamthonkiat et al. 2005; Shao et al. 2001; Xiao et al. 2005, 2006), statistical methods (Frolking et al. 2006; You and Wood 2005) or a combination of these (Dawe et al. 2004; Frolking et al. 2002; Leff et al. 2004; Monfred et al. 2008). The results of such studies showed past or present paddy rice cover over Asia on a continuous scale, and have been used in analyses of climate and trace gas emissions in Asia. However, all of the above-mentioned studies have a noticeable shortage of time horizons, and are limited in their usefulness for the study of future scenarios since they were unable to address possible future changes in Asia paddy rice. To assess the consequences of cultivation practices for food production and the health of the environment, understanding and modeling future changes in Asia paddy rice is critical and has thus attracted much attention from the scientific community. This study thus attempts to develop a modeling approach to simulate future dynamic changes in sown areas of Asia rice.

Crop choice decision model

The general hypothesis of the modeling approach is that the sown area of particular crops is linked directly to human decisions on crop choices for farmland. Land users make their decisions on crop choices in the context of their own strategies or rules, which affects the conversion of land from the cultivation of one crop to another as well as the preservation of land in its current state. Thus, through capturing the essential features of individual human decision processes regarding crop choices, it is possible to track and estimate changes in the crop sown areas over time and space (Wu et al. 2007a, 2008). However, the possibilities of making a living for farmers are broader than agriculture alone. For the sake of simplicity, we assume that farming is the main source of household income; hence, the research question is why households cultivate a certain crop at a certain location and how they adjust their crop choices in response to changes in the coupled human–environment system (Wu et al. 2007b).

Under the aforementioned assumption, a crop choice decision model was developed here within the framework of Action-in-Context (AiC) with the aim of understanding the crop choice behavior of land users (Overmars et al. 2007a). AiC was originally designed for studies that put human actions, especially in the environmental field, into context to gain insight into the underlying causes of these actions. The idea of AiC is to start with the actions to be explained, to identify the decision-making actors directly causing the action, then to study the range of options available to the actors and the motivations attached to these options (Overmars et al. 2007b). Using these concepts, the crop choice decision model was structured as shown in Fig. 1, where the arrows stand for the direction of causal relations; each layer is described in more detail below.

Actor, action and effect

The actors are social entities that exercise a significant decision-making capacity on the action. An actor can represent any level of organization and is not necessarily an individual. The actors considered in this study are those households that have control over a piece of cropland that they can possibly cultivate in the context of their own strategies and rules. The analysis of actions focuses on the crop choice decisions of these actors. The effect is the dynamic change in sown areas of Asia rice crop. An example of the relations in the first layer is a household (actor) who decides to grow rice (action) instead of wheat,

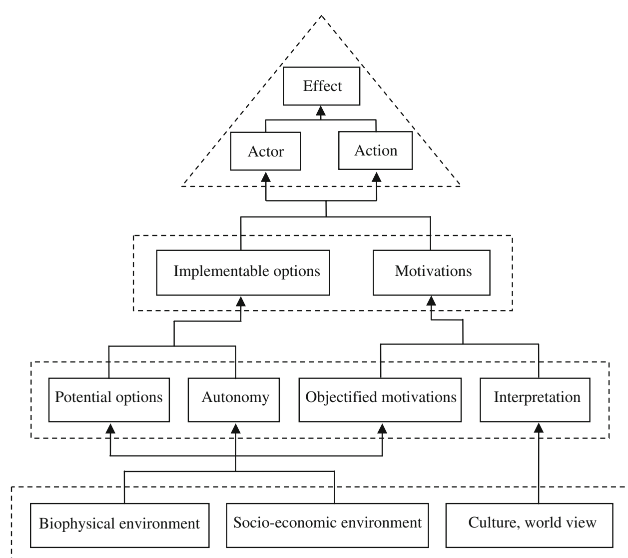

Fig. 1 Structure of the crop choice decision model under the Action-in-Context (AiC) framework

leading to changes in sown areas for rice and wheat (effect).

Implementable options

Implementable options are built up from "potential options" and "autonomy" in the third layer. Potential options are all options that the actors are aware of during their actions. According to the statistical database of the Food and Agriculture Organization (FAO), the four crops of rice, maize, wheat and soybean account for nearly 85% of the cereal croplands in Asia. Only these four major crops were taken into account in this study, and they represent the potential options available to households in the process of crop choice decision.

However, not all of these potential options can be implemented. The difference between the implementable options in the second layer and the potential options in the third layer is the difference between what the actor really can do as opposed to what the actor might do if he had the possibility. This difference is determined by the autonomy of the actor (Overmars et al. 2007a). This autonomy consists of resources and restrictions, which together determine which potential option can be implemented by an actor. In this study, the implementable options were defined by the multiple cropping systems and crop combinations. Using these cropping systems, different households across Asia may choose between possible farming systems and make their decisions on crop choices.

Motivations

Motivations are the merits of the options under consideration, which are used by the decision-maker to evaluate the attributes of choice options and determine a choice. These motivations are separated into "objectified motivations" and "interpretations" in the third layer (Overmars et al. 2007a). The objectified motivations are all decision-relevant characteristics of options that are easily quantified, such as economic costs and benefits or caloric value of produced foods. Interpretation is shaped by cultural and psychological opinions and ways of looking at the options that give weight, coherence, shape and color to the objectified motivations. Together, they form the motivations as interpreted by the actor.

In an attempt to build a large-scale crop choice decision model using a simple method, this study focused mainly on the objectified component of motivations. We use the term "utility" to describe the objectified motivations of individual crop options, and the term "discrete choice analysis" (DCA) to define a mathematical function that expresses the preferences of a household's crop choices (Wu et al. 2007a, 2008). Using these relative crop utilities, farmers seek to maximize their income within the constraints of their situation by allocating their lands to those crop cultivation activities that they perceive will provide the greatest return or that will carry the least risk. The allocation of land to specific crop types is then translated into the conversion of an area from one crop coverage to another. The utility (U_i) of each possible crop is assumed to comprise two parts:

$$U_i = V_i + \varepsilon_i \quad (1)$$

where V_i is the systematic and observed component of the latent utility for crop i, and ε_i is the random or "unexplained" component.

Because of the random component, scientists can never expect to predict choices perfectly. This leads to expression of the probability of choice. Assuming that the random error terms are distributed independently and identically and follow the Gumbel distribution, the probability that a crop i is chosen for cultivation can be estimated using the Multinomial Logit model (Seo and Mendelsohn 2008; Wang et al. 2007):

$$P_i = \mathrm{e}^{V_i} \Big/ \sum_{i=1}^{N} \mathrm{e}^{V_i} \quad (2)$$

where i denotes the crop types used for analysis (i = 1, 2, …, N), P_i is the probability for crop type i, and V_i is the observed utility of crop type i, which can be stated as:

$$V_i = a_i + \sum_{j=1}^{M} b_j x_j \quad (3)$$

where a_i is an alternative specific constant for crop type i, j is the number of explanatory variables (j = 1,2, …, M), x is the explanatory variable, and b_j is the coefficient to be estimated for the variable x_j (Mcfadden 1973).

The aforementioned analysis interprets that the impetus for changes in sown crops depends on the difference in their utilities, where a change in crop utilities may drive changes in crop choice decisions, resulting in further changes in crop sown areas over time and space.

Human–environment system

The elements in the third level are usually determined by "biophysical environment", "socio-economic environment" and "culture and world views" in the fourth layer (Overmars et al. 2007a). Biophysical environment represents the local temperature, rainfall, topography and soil conditions, which determine the direct options and benefits of farming activities in the third layer, while socio-economic environment represents the macro-level demographic (e.g., rural population density), economic (e.g., farming income per capita, agricultural mechanization and international trade price), technological (e.g., irrigation, fertilizers and pesticides) conditions that influence the costs and efficiency of a certain crop cultivation either directly or indirectly. These two together form the coupled human–environment system, under which crop choice decisions are made.

Many driving forces in the coupled human–environment system can impact crop choice decisions, largely through modifying the utilities of individual crops. However, it is not possible to include all of these factors in our model, especially when modeling land-use change over large areas. Instead, we generally used some proximate variables that represent the underlying driving factors (Verburg et al. 2002). In this modeling approach, some variables that were highly correlated to others were excluded from the model analysis for the sake of simplification and the elimination of computation redundancy. For instance, crop yield itself is a measure of performance of the crop plant, which is enhanced or reduced by biophysical factors (e.g., temperature, rainfall, soil and topography) as well as by agricultural management practices such as irrigation and fertilizing; therefore, crop yield can be used to reflect the impacts and interactions of most biophysical and agricultural management variables. Finally, four main variables, namely, crop yield, crop price, rural population density and road accessibility, were selected as the explanatory variables for computation of crop utilities in the crop choice decision model.

Preparation of input data

The input data required in this study is listed in Table 1. Of these data, crop yield, crop price, population density and road accessibility data were input directly into the crop choice decision model for the calculation of crop utilities. The potential multiple cropping systems determined the different crop choice options for households, while global land cover and irrigation datasets affected the allocation of crop choices. The FAO statistical database was used for model validation.

Crop yield was estimated with the GIS-based Environmental Policy Integrated Climate (EPIC) model (Tan and Shibasaki 2003). The GIS-based EPIC model is a biophysical process-based model that simulates spatial and temporal dynamics of agricultural production and related processes such as weather, hydrology, nutrient cycling, tillage, plant environmental control and agronomics. An earlier application of GIS-based EPIC by the authors of this paper has shown that EPIC-simulated crop yields agree well with measured crop yields for the same four crops at a global scale (Wu et al. 2007a). A detailed description of the GIS-based EPIC model can be found in Wu et al. (2007a, 2008), while a detailed description of the original EPIC model can be found in Williams et al. (1989). Crop price was assessed by a crop price model, the International Food Policy and Agricultural Simulation (IFPSIM) model. The IFPSIM is a multi-commodity, multi-regional and multi-period world agricultural trade and policy simulation model developed and designed based on the Ohga Model Building System (OMBS; Ohga and Yanagishima 1996). It is a partial equilibrium and interactive model, allowing for the simultaneous determination of supply, demand, trade, stock levels and prices for 14 commodities of the world (Ohga and Gehlar 1993).

Rural population density data were generated from the Landscan Global Population Database, and road accessibility data were derived from the ESRI product digital chart of the world database. The potential multiple cropping systems for the four crops in Asia were defined by matching temperature and water requirements of individual crops and crop combinations with the agro-ecological environment available for crop growth (Wu et al. 2007a). The 1 km IGBP-DISCover global land cover dataset was downloaded from the IGBP database, and global irrigation data was taken from Döll and Siebert (2000). For future simulation, we assumed these datasets unchanged since it is not possible to collect these data for the future.

Owing to the large degree of variation in data from sources with different spatial and temporal resolutions, it

Table 1 Input data used in this study

Dataset	Time period	Data sources
Crop yield	1995–2035	Simulated by the GIS-based EPIC model (see Tan and Shibasaki 2003)
Crop price	1995–2035	Simulated by the IFPSIM model (see Ohga and Yanagishima 1996)
Rural population density	1998	http://www.ornl.gov/sci/landscan/
Road accessibility	1993	http://www.maproom.psu.edu/dcw/
Multiple cropping systems		Generated by Wu et al. (2007a)
Global map of irrigated areas	1995	http://www.geo.uni-frankfurt.de/ipg/ag/dl/forschung/global_irrigation_map/index.html
IGBP-DISCover global land cover dataset	1992–1993	http://edcsns17.cr.usgs.gov/glcc/globe.int.html
FAO statistical database (FAOSTAT)	1995–2004	http://faostat.fao.org/

was necessary to perform a procedure of data preprocessing and standardization. To do this, all spatial data were clipped to the Asian region and converted into GIS grid data with a cell size of 6 min by 6 min in a standard GIS software environment (ESRI ArcGIS 9.1). The C programming language was used to develop the model program, allowing the model to directly access the multiple input data in GIS grid format from numerous sources.

Model validation

The validation approach used here was to compare model estimates with independently recorded historical data at a national scale. The resulting similarity between predicted and measured values at a national level can improve our understanding of whether the simulated output is following the trend of a reported aggregate average. To do this, we ran the model for the period of 1995–2004 and compared the simulation results with a time series of FAO statistical data.

Figure 2 shows the comparison between model simulations and FAO statistical data on aggregated rice sown areas for all Asian rice-producing countries. It can be seen that, although there were some places where the model simulation deviated more or less from the reported FAO values, in general the simulated and reported values were similar. The trend line was close to the 1:1 line, and the R^2 value was higher than 0.9.

Furthermore, comparison of the five major rice-producing countries (India, China, Indonesia, Bangladesh and Thailand) in Asia is shown in Fig. 3. The simulated areas and the statistical areas were also quite comparable. The model estimates of rice sown area for India, Bangladesh and Thailand had a higher correlation with the corresponding FAO historical data, while those for China and Indonesia had a relatively higher deviation from the aggregated FAO data. The main reason for the difference between the simulation and the observed data was possibly the uncertainty in estimations of crop yield made by the GIS-based EPIC model and those of crop price made by the IFPSIM model. Most of the GIS-based EPIC crop parameters established by the United States Department of Agriculture, Agricultural Research Service were not modified and were applied directly in this study, which may have resulted in some underestimation or overestimation of the crop yields that was then used by the crop choice decision model. In addition, uncertainties or bias in the reference data can also distort the performance of model validation in some way. For instance, it has been well documented that China's local officials tend to underreport the area of cultivated crops in order to evade state production quota and taxes, or to inflate the average yields (Lin and Ho 2003). This may result in an underreported total area for cultivated crops in China for use in our model validation. Considering the evaluation results and analysis described above, the simulated results are regarded as satisfactory for large-scale modeling, and the modeling approach appears to be applicable to the analysis of long-term future scenarios.

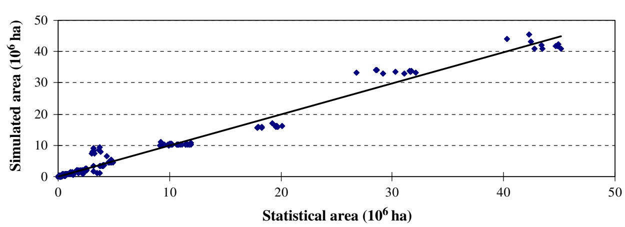

Fig. 2 Time-series validation of the crop choice decision model for all rice-producing countries in Asia

Future simulation results

The following demonstrates the potential uses of this modeling approach for assessing future changes in the sown areas of Asia rice crop under a given scenario. The model application was designed to run over a period of approximately 30 years with a 5-year time increment, starting at the year 2005, and to analyze potential changes in sown areas for Asian paddy rice.

Temporal changes in total sown areas for Asian rice

Figure 4 presents the general trend of changes in total sown areas for Asian rice as predicted by the model for the period 2005–2035. It can be seen clearly that the rice crop in Asia exhibits a constant growth in total sown area after the year 2010; in particular, the model shows a substantial increase during the later period of the model simulation. The total rice sown areas in Asia are predicted by the model to increase to 144 million ha by 2035, with a growth rate of 16% with respect to that (124 million ha) in 2005.

Regional variations in rice area changes

Figure 5 shows the simulated geospatial distribution of paddy rice fields across Asia in 2005 (Fig. 5a) and 2035 (Fig. 5b). It is clear that rice cultivation in Asia covers a large spatial domain and a wide range of landscape types, spanning from India and Nepal in the west to Japan and Korea in east, and from the northeast China in the north to Indonesia in the south. Paddy rice fields are concentrated largely in the valleys and deltas of the major rivers in the region, such as the Mekong and Ganges river basins, and the Yangtze river regions. Such a large area contains a

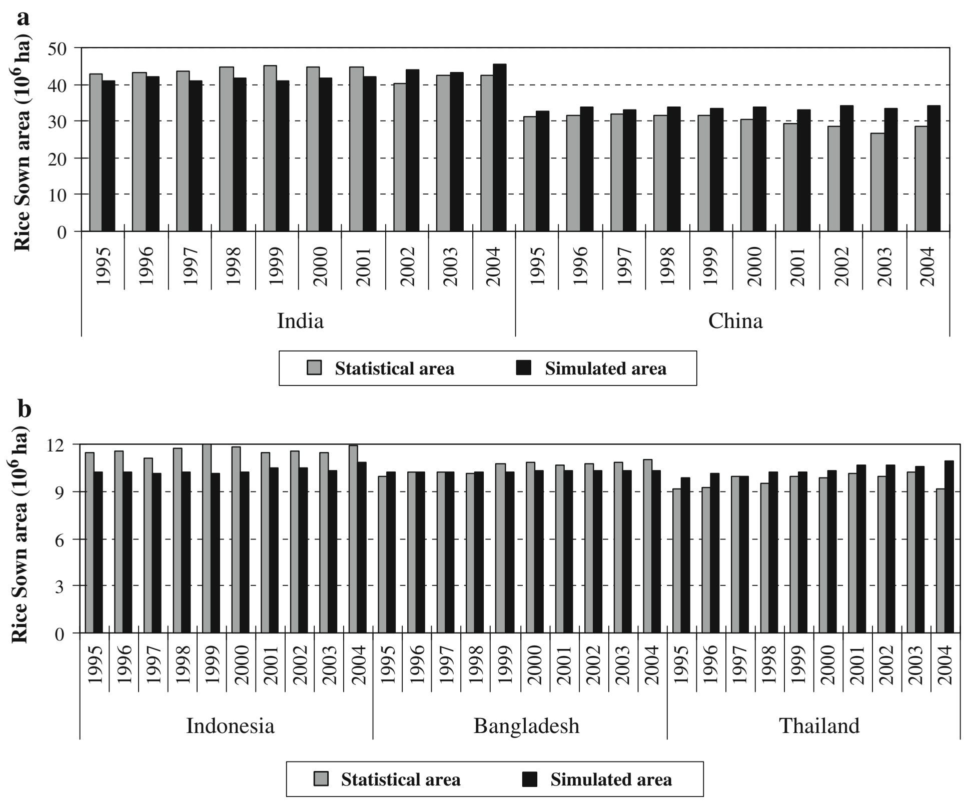

Fig. 3 Time series validation of the crop choice decision model for **a** India and China, and **b** Indonesia, Bangladesh and Thailand

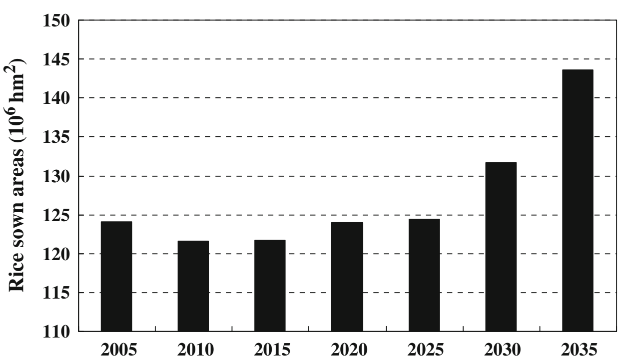

Fig. 4 Temporal changes in total sown areas for Asian rice during the period 2005–2035

wide variety of climatic zones, ranging from the temperate zones in the north to the tropical and subtropical zones in the southeast. With such a large variation in landscape and climate in the rice-growing region of Asia, a large number of unique rice farming methods have also evolved, based on farming type (irrigated, rainfed, and deepwater), crop management (single cropping and multiple cropping) and seasonality (wet season and dry season). These differences in rice farming systems lead to great variation in the rice sown areas across regions in Asia.

Figure 6 illustrates the simulated sown areas and their predicted changes for Asian rice in different regions of Asia during the period 2005–2035. Rice sown areas were projected to reach 70, 41 and 33 million ha for the south, east and southeast Asia, respectively, by 2035, with growth rates of 7.6, 18 and 20%, respectively, when compared with 2005. Although all three regions showed an increasing trend in rice sown areas, there were some differences in the sown area changes between them. The sown areas of rice were predicted to decrease slightly at different rates from 2005 to 2010 in each of the three areas. Thereafter, the rice sown areas in south and southeast Asia showed a stable and continuous increase, in particular, during the later period of model simulation. The changes in rice sown areas for east Asia were different from other two regions. The rice areas of east Asia declined gradually until the year 2025, with a decrease rate of 12.5% relative to 2005. After 2025, its sown areas of rice showed an uptrend, outweighing the 2005 level in 2030.

Rice area changes for major producing countries

In Asia, those countries whose total rice sown areas are more than 10 million ha are mainly in India, China, Indonesia, Thailand and Bangladesh. These countries are the major rice producing states of the world, and adding their areas together gives about 82% of global total sown area of rice. Thus, understanding the possible dynamics in the rice sown areas of these countries is of great importance. Figure 7 presents the changes in rice sown areas for these five countries for the period 2005–2035.

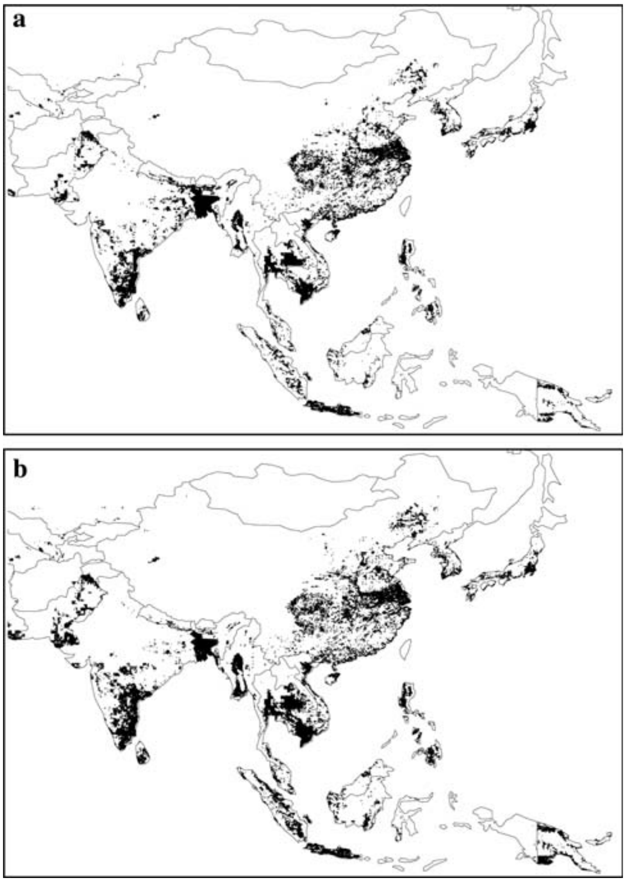

Fig. 5 Geospatial distribution of Asia paddy rice in **a** 2005 and **b** 2035

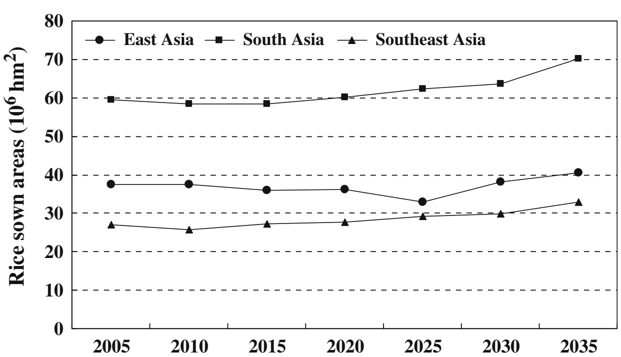

Fig. 6 Rice area changes in different regions of Asia during the period 2005–2035

India is the country with the largest rice sown areas worldwide. Rice-growing areas in India are primarily in the eastern coastal regions and the two great river basins in the northern part of the country: the Ganges and the Brahmaputra (Fig. 5). It can be seen from Fig. 7 that rice areas in India showed a substantial increase during the simulation period except in the early stage of the simulation period, where there was little decrease in rice areas. Rice areas in India were projected to be about 58 million ha by 2035, accounting for 40% of total rice sown area in Asia. Rice agriculture in China was concentrated in major lake regions (Tai Lake in the east, Poyang Lake and Dongting Lake in the central), the middle and lower reaches of the Yangtze River, and large plains (e.g., the Song-Liao and San-Jiang plains in the northeast, Chendu Plain in the southwest; Fig. 5). Although sown areas of rice in China were predicted to increase to 37 million ha by 2035, changes in sown areas generally fluctuated instead of increasing linearly. Rice sown areas in China declined in the early stage, in particular decreasing by about 8% in 2025 relative to 2005. On the contrary, during the late period, rice sown areas in China increased rapidly.

Nearly half of the rice land in Thailand is located in the northeast interior region (Fig. 5), where the majority of the rice fields are rainfed. In Bangladesh, rice ecosystems are dominated by rainfed (over 50% of the rice area) and irrigated systems, although significant amounts of upland and deepwater rice still exist. Nearly 50% of the cropland is double cropped and 13% is triple cropped (Maclean et al. 2002). In the model, over the next 30 years the national rice areas of Thailand and Bangladesh remained stable, slightly changing from 11 million ha in 2005 to 12 million ha in 2035 and from 10 million ha in 2005 to 11 million ha in 2035, respectively. While each of Indonesia's five main islands has some areas of intense rice production, heavily populated Java is the most productive rice area (Fig. 5). Similar to Thailand and Bangladesh, rice areas in Indonesia showed little change during the early period of model simulation. However, after 2020, rice crops in Indonesia showed a significant increasing trend in sown areas over time, with the national rice areas predicted to be about 15 million ha by 2035.

The different patterns of change in rice areas in Asian countries were due mainly to variations in crop yield and crop price for different countries. This interprets, to some extent, the competition between rice crop and other crop types under different cropping systems, since only a finite amount of the Earth's surface is available for agricultural land use. As the crop yield or crop price varies in space and time, rice crop may gain or lose either a physical or an economic advantage over other crop types and, therefore, will be more or less likely to be selected for cultivation or to be replaced by other crops by farmers. In addition, the crop choice model appeared to be more sensitive to crop price than to crop yield. This reflects the fact that changes in rice sown areas are generally related more closely to fluctuations in crop price than to fluctuations in crop yield. This can probably be attributed to the model assumption that households are autonomous and are capable of perceiving changes in the social system. Thus, households are more easily and intuitively able to regulate their crop choices in response to changes in crop price, which directly

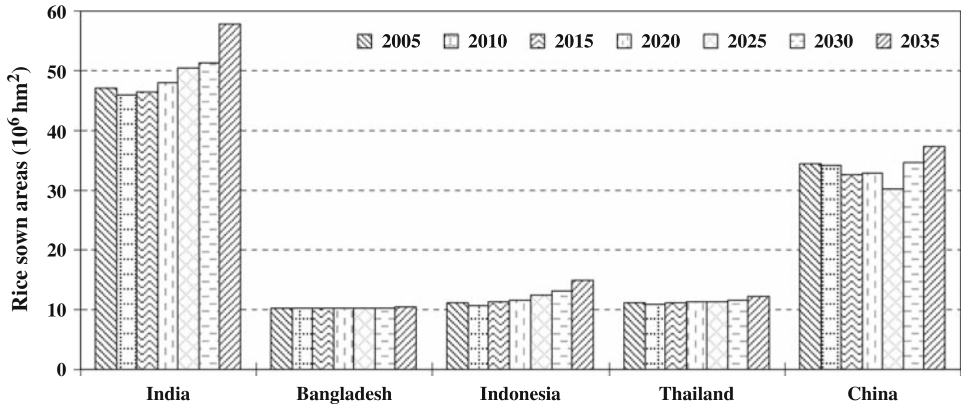

Fig. 7 Rice area changes in major rice producing countries in Asia during the period 2005–2035

determines the profits or returns of crop cultivation on their land. By contrast, households react gradually in response to changes in crop yield, since they may take a period of time to understand new crop varieties or breeding measures that result in yield increases.

Implications of rice area changes for agricultural sustainability in Asia

With increasing population and growing demand for food in Asia, cropland protection for agricultural production is of the utmost importance to ensure food security and agricultural sustainability. According to the FAO definition, food security comprises four key dimensions of food supplies: availability, stability, accessibility and utilization (Ericksen 2008). Our simulation results showed that, although some regions in Asia experienced a decrease in rice areas for a certain period, paddy rice in Asia generally presented an upward trend pattern in the next 30 years. This increase in Asia rice areas could potentially increase total food production and availability and thus offset to some extent the pressure of increasing need from the population increase in coming years. However, it should be noted that, as a consequence of global and regional climate change, increases in the frequency and severity of extreme events (such as cyclones, floods, hailstorms and droughts) may bring greater fluctuations in crop yields and higher risks of landslides and erosion damage, and thus adversely affect the availability and stability of food production, in particular for south and southeast Asia. The cyclones that occurred in Bangladesh last year and in Myanmar this year highlight precisely this issue.

Moreover, most Asian countries are less developed, and have large poor and undernourished populations. With the continuous increase in food prices, the crucial issue for food security is not whether food is "available", but whether the monetary and non-monetary resources at the disposal of the population are sufficient to allow them access to adequate quantities of food. As a result, national self-sufficiency is neither necessary nor sufficient to guarantee food security at the individual level. Note that Singapore, where agriculture is non-existent, is not self-sufficient but their populations are quite food-secure, whereas India is self-sufficient but a large part of its population is not food-secure (Schmidhuber and Tubiello 2007). In addition, the lack of sanitary conditions and the various associated diseases, such as malaria, and diarrhoea and cholera, in the tropical and subtropical regions of Asia also affect food safety directly and lower the capacity to use food effectively. Therefore, many less developed countries in Asia are very vulnerable and are exposed to a higher degree of food insecurity.

Given this situation, on the one hand, cultivation intensification will be the dominant means for increasing production in the future as there is little new suitable land that can be brought into cultivation for many regions in Asia. Increasing the number of crops sown on a particular area of land or by increasing the yield per unit area of individual crops by continued technological developments, or both, is expected to be the main way to increase food production to meet the demands of food security (Gregory et al. 2005). On the other hand, development of effective adaptation to changing environments in Asia is an increasingly urgent agenda for most countries (Lobell et al. 2008). These can involve management-level adaptation options such as investing in agricultural inputs such as fertilizer rates, irrigation and improved varieties/species, altering the timing of cropping activities, improving the effectiveness of pest and weed control, and water and soil management practices. However, adaptations at this level can be influenced strongly by government policy decisions to establish or strengthen conditions favorable for effective adaptation activities through fostering freer trade and promoting investments in new technologies and infrastructure, building adaptation capacity of user community and institutions, and in general modifying the decision-making environment under which management-level adaptation activities typically occur (Brown and Funk 2008; Howden et al. 2007). All these can help to increase steady local and international production, improve fast access to food supplies, and provide secure and stable food supplies for the future.

Discussion and conclusions

This paper described a modeling approach for simulating possible future changes in sown areas of paddy rice in Asia. The basic hypothesis was that decisions on crop choices made by farmers mediate the impacts of biophysical and socio-economic aspects on changes in agricultural land use. This basic hypothesis was considered when developing the model, which attempts to establish the dynamic interface of a human–natural environment relationship in an integrated modeling framework.

After its construction, empirical validation using data from historical statistics indicated that the model is reliable for addressing the complexity of current agricultural land-use change, and that it has the capacity to be used for investigating long-term scenarios and applications in the future. Taking 2005 as the starting year, the model was applied to a simulation of future scenarios until 2035 in time increments of 5 years. The simulation results showed the temporal and spatial variations in rates and direction of changes in the sown areas of Asia paddy rice. The model outcomes can help understand and explain the causes, locations and consequences of land-use change, and can provide significant support for land-use planning and policy making (Rounsevell et al. 2005).

However, the model also contains some uncertainties and there are several caveats that should be kept in mind. First, the model focuses on four major crops and does not consider new crops that might be introduced into the crop choices. The model therefore underestimates the likely substitution available in crop choices. Moreover, this analysis assumed that adaptations of crops can take place as needed. For example, farmers can switch from rice crop to another crop as driving factors change. However, this may not be the case if the adjustment requires a heavy capital investment. These adaptations will not be instantaneous and they may also take farmers a long time to make (Seo and Mendelsohn 2008). Second, we used a simplified modeling approach based on a few assumptions regarding the driving factors behind land-use change. Some other causes, e.g., policy change (Van Meijl et al. 2006), technological development (Verburg et al. 2006) and social preferences (Serneels and Lambin 2001), which may also have a great influence on changes in crop sown areas, were not taken into account in this study. Large changes in these omitted factors may alter the simulation results. Third, when this crop choice model was used for future scenario analysis, the input data had to be changed to explore or depict these future scenarios according to a set of subjective rules. The inherent uncertainty and limitations of these input values can bring about some bias in the outputs from model simulations (Verburg et al. 2006; Wu et al. 2008). Furthermore, even when the causal relationship between the driving factors and crop area changes was well constructed, future changes in crop choices may not necessarily be described by the relationships derived from past and present observations, as land-use activities are so dynamic and mechanistic understanding of land-use change is insufficient (Wu et al. 2007a; Rounsevell et al. 2006). Future studies should address these issues to provide future understanding of the processes of crop choices made by individual households.

Acknowledgments This study was supported financially by the Ministry of Education, Culture, Sports, Science and Technology of Japan under its DIAS (Data Integration and Analysis System) project, by National High Technology Research and Development Program of China (40930101 and 40971218), and by the Foundation for National Non-Profit Scientific Institution, Ministry of Finance of China (2009-IARRP-25). All persons and institutes who kindly made their data available for this analysis are acknowledged. Last but not least, we thank the anonymous reviewers for their constructive comments on an earlier version of the manuscript.

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