Aus dem Institut für Landnutzung
der Agrar- und Umweltwissenschaftlichen Fakultät

Agricultural land use and associated nutrient flows in peri-urban production systems

Dissertation
zur
Erlangung des akademischen Grades

doctor agriculturae (Dr. Agr.)

an der Agrar- und Umweltwissenschaftlichen Fakultät
der Universität Rostock

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Rostock, den 22. Dezember 2009

urn:nbn:de:gbv:28-diss2010-0152-0

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Day of Examination:	25 June 2010

Executive summary

Urbanisation in the developing world is accelerating more rapidly than ever before, thus leading to a significant increase in food demand in the coming decades. Food export from rural to urban regions exacerbates the problem of soil nutrient mining, soil fertility decline and degradation, while a large fraction of these products finally ends up as waste in waterways or on landfills. Transport of bulky organic waste to rural areas is rather unlikely for reasons of associated costs. Urban and peri-urban agriculture could thus play a pivotal role as a recipient of organic solid and liquid waste from inner-urban areas. It could help overcome the waste problem, save limited resources and increase food security. However, recycling and reuse of urban organic waste in peri-urban agriculture requires planning tools flexible enough to capture the diversity of farming systems and to assess their nutrient status over spatial and temporal scales. This work aims at developing a methodology to determine nutrient flows and budgets at farm, village and communal level of peri-urban agricultural production systems by taking into account spatial and temporal variability of crop and nutrient management. The methodology should be further discussed in the context of recycling and reuse of organic waste products in peri-urban agriculture.

Environment and social rules and regulations not only play a key role in land use practices, but influence combination, frequency and sequence of crops in rotation. Crop rotations are usually associated with their spatial arrangement on farms or in management units and cause rather fixed patterns of production sources. Knowledge of the presence/absence of specific crop rotations in the spatial context could add an important temporal component to site-specific crop and fertiliser management. Based on survey data of a farming system in a peri-urban commune of Hanoi, Vietnam, statistical models on proximate causes for specific crop rotations to occur were developed and tested with an extensive set of explanatory variables using a logistic regression procedure. Different crop rotations were evaluated, i.e. staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. The results revealed that distance and perceived soil fertility best explained the presence/absence of crop rotations. Models based on path or Euclidian distance performed better than those based on built-up buffer distance. By using Euclidian distance and perceived soil fertility achieved 79% correct predictions and an area under curve (AUC) of 0.84 when tested on SSF. SSC and CCC rotations reached 72% and 90% correct predictions, an AUC of 0.74 and 0.75.

Drivers of spatially explicit crop rotations have the potential to predict spatial and temporal changes in agricultural land use.

Continuous use of excess amounts of fertiliser leads to soil and water pollution. Conversely, large fertiliser deficits over a mid or long-term period result in soil fertility degradation. Site-specific nutrient management (SSNM) is suggested where substantial differences between soil fertility levels exist. Crop rotations play an important role in site-specific management of agricultural land and allow farmers to profoundly modify the soil environment. Knowledge of the patterns related to nutrient management of crop rotations could help combat soil fertility degradation. Nitrogen fertiliser inputs were used as indicators for nutrient flows to staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. Average organic, inorganic and total nitrogen fertiliser inputs of SSF vs SSC & CCC, and average total nitrogen input of SSC vs CCC differed significantly. Rank transformed ANCOVA with covariates built-up buffer distance, road buffer, soil fertility, water availability during the 1st and 3rd season, relative elevation topography, plot size, and farm livestock number were tested for their explanatory power. Thereby, built-up buffer distance and plot size explained much of the variation. However, overall explanatory power was low to moderate, reaching highest with 51% in the case of SSC & CCC. Remaining variation in rotations was partially explained by different fertiliser application patterns between crops. Spatially explicit crop rotations added an important temporal component and improved the understanding in nutrient flow patterns.

Where biophysical and socio-economic processes lead to spatial fragmentation of agricultural land, such as in rapidly changing peri-urban environments, remote sensing offers an efficient tool to collect land cover/land use (LCLU) data for decision-making. The usefulness of object-based image analysis related to land cover/land use classification was assessed on the basis of Quickbird high spatial resolution satellite data of a peri-urban commune of Hanoi. Accurate segmentation of shape and size of an object enhanced classification with spectral, textural, morphological, and topological features. A qualitative visual comparison of the classification results revealed successful localisation and identification of most LCLU categories; however, a quantitative evaluation resulted in an overall accuracy of only 67% and a kappa coefficient of 0.61. Object-based classification of high spatial resolution satellite data proved a promising approach for LCLU analysis at village level. Nevertheless, delineation of field boundaries and LCLU diversity with more spatially extensive datasets still remain a challenge.

Since successful classification of crops is greatly influenced by field boundary delineation accuracy, a classification procedure based on Quickbird satellite image data was developed and tested to enable LCLU mapping of highly diversified peri-urban agriculture at sub-communal and communal level (7 km^2). Accuracy of field boundary delineation was evaluated by an object-based segmentation, a per-field and a manual classification, along with a quantitative accuracy assessment. Classification at sub-communal level revealed an overall accuracy of 84% with a kappa coefficient of 0.77 for the per-field vector segmentation compared to an overall accuracy of 56–60% and a kappa coefficient of 0.37–0.42 for object-based approaches. Per-field vector segmentation was thus superior and used for LCLU classification at communal level. Overall accuracy scored 83% and the kappa coefficient 0.7. In small-scale, intensified agricultural systems, such as in peri-urban areas, per-field vector segmentation and classification achieved yet higher classification results.

Tools developed to manage resource flows of towns and cities provide a good overview of the process involved, however, they usually neglect the important spatial component. The methodology described makes use of three main components: farming system survey, GIS and remote sensing. To explore spatially and temporally explicit nutrient flows, the following four analytical steps are proposed: (i) analysis of land use I, (ii) analysis of crop rotations, (iii) analysis of nutrient flows, and (iv) analysis of land use II. Outputs of the various steps are then used in the modelling of spatially explicit crop rotations and associated nutrient flows. They provide valuable data for environmental monitoring and a solid basis for developing spatially explicit organic waste reuse scenarios.

Keywords: crop rotation, cropping pattern, nutrient balance, nutrient flow, Hanoi, land cover/land use, remote sensing, soil fertility decline, spatial and temporal, waste reuse, Vietnam

Zusammenfassung

Die Urbanisierung in Entwicklungsländern nimmt schneller zu als je zuvor. Demzufolge wird in urbanisierten Gebieten der Bedarf an Nahrungsmitteln in den kommenden Jahrzehnten stark ansteigen. Nahrungsmitteltransporte vom ländlichen Raum in die Stadt verstärken das Problem des anhaltenden Nährstoffentzugs und führen zu einem Rückgang der Bodenfruchtbarkeit und zu Degradation. Grosse Teile dieser Nahrungsmittel enden schlussendlich als Abfall in Entwässerungsgräben oder auf Müllhalden. Die Rezyklierung und Rückführung des umfangreichen organischen Abfalls in die ländlichen Gebiete ist wegen der hohen Transportkosten eher unwahrscheinlich. Städtische und stadtnahe Landwirtschaft könnten vor diesem Hintergrund eine wichtige Rolle hinsichtlich der Abnahme von organischen Substanzen (in flüssiger und solider Form) wahrnehmen, limitierte Ressourcen effizienter nutzen, die Nahrungsmittelversorgungssicherheit erhöhen, und dabei zur Lösung des Abfallproblems in den Agglomerationen von Entwicklungsländern beitragen. Allerdings bedarf es für die Rezyklierung und Wiederverwendung von organischen Abfällen in der stadtnahen Landwirtschaft entsprechender Planungsmittel, die genügend flexibel einsetzbar sind, um die Vielfalt der Anabausysteme und deren Nährstoffflüsse zeitlich und räumlich zu erfassen. Die vorliegende Arbeit verfolgt das Ziel, eine Methode zur Abschätzung der Nährstoffflüsse auf der Ebene von Betrieben, Dörfern und Kommunen zu entwickeln und dabei die zeitliche und räumliche Variabilität der Landnutzung und des Nährstoffmanagements zu berücksichtigen. Diese Methode soll weiter im Kontext der Rezyklierung und Wiederverwendung von organischen Abfallprodukten in der stadtnahen Landwirtschaft diskutiert werden.

Umweltaspekte, Vorschriften und gesellschaftliche Regeln spielen eine wichtige Rolle in der Landnutzungspraxis und beeinflussen Kombination, Häufigkeit und Abfolge von Kulturen einer Fruchtfolge. Normalerweise sind Fruchtfolgen mit der räumlichen Anordnung von Kulturen auf landwirtschaftlichen Flächen verbunden, binden Produktionsressourcen und führen zu Mustern im Management. Spezifisches Wissen bezüglich des Auftretens von bestimmten Fruchtfolgen im räumlichen Kontext könnte eine wichtige temporale Komponente für das standortbezogene Kultur- und Düngermanagement darstellen. Auf der Basis von Landnutzungsdaten, erhoben in einer stadtnahen Kommune von Hanoi, Vietnam, wurden statistische Modelle zur Vorhersage von bestimmten Fruchtfolgen entwickelt. Eine Vielzahl

von unabhängigen Variablen wurde in einer logistischen Regression gestestet. Folgende verschiedene Fruchtfolgen wurden evaluiert: ’grundnahrungsmittelbetonte’ (SSF), ’marktfruchtbeeinflusste’ (SSC) und ’marktfruchtdominierte’ (CCC). Die Resultate zeigen, dass die Entfernung eines Feldes und die vom Bauern wahrgenommene Bodenfruchtbarkeit das Auftreten einer Fruchtfolge am besten erklären. Modelle, die auf der Pfad- oder der Euklidischen Distanz basieren, schnitten besser ab als das Modell, das auf der ’Ring Buffer’-Distanz fusst. Das Modell mit den Variabeln ’Euklidische Distanz’ und ’wahrgenommene Bodenfruchtbarkeit’ erreichte 79% korrekte Vorhersagen und eine Fläche unter der Kurve (AUC) von 0.84 für die Fruchtfolge SSF. Die Fruchtfolgen SSC und CCC erzielten 72% und 90% korrekte Vorhersagen, während die Fläche unter der Kurve die Werte 0.74 und 0.75 erreichte. Die Einflussgrössen ’Distanz’ und ’Bodenfruchtbarkeit’ sind demnach die zentralen Faktoren für die Vorhersage von räumlicher und zeitlicher Landnutzung.

Anhaltendes Ausbringen von überhöhten Düngermengen führt zu Boden- und Wasserverschmutzung. Umgekehrt kann eine starke Unterversorgung mit Nährstoffen über lange Zeit zu einem Rückgang der Bodenfruchtbarkeit führen. Bei grösseren Unterschieden in der Bodenfruchtbarkeit wird ein standortgerechtes Nährstoffmanagement vorgeschlagen. Fruchtfolgen spielen dabei eine wichtige Rolle und ermöglichen Bauern, den Boden und dessen Umfeld substanziell zu beeinflussen. Bessere Erkenntnisse über die Nährstoffflüsse in diesen Fruchtfolgen können einen Beitrag zur Vermeidung der Bodendegradation leisten. Stickstoffgaben wurden als Indikator für die Nährstoffflüsse in grundnahrungsmittelbetonten (SSF), marktfruchtbeeinflussten (SSC) und marktfruchtdominierten (CCC) Fruchtfolgen untersucht. Im Durchschnitt waren die organischen, anorganischen und gesamten (organisch + anorganisch) Stickstoffgaben der Fruchtfolgen SSF vs. SSC & CCC, sowie die durchschnittliche gesamte Stickstoffgabe von SSC vs. CCC signifikant unterschiedlich. Im Rahmen einer Rang transformierte Kovarianzanalyse wurden die Kovariaten ’Ring Buffer’, ’Weg Buffer’, ’wahrgenommene Bodenfruchtbarkeit’, ’Wasserverfügbarkeit in der 1. und 3. Anbauperiode’, ’relative Geländetopographie’, ’Schlaggrösse ’ und ’Tierzahl’ getestet. Ring Buffer und Schlaggrösse erklärten teilweise die Variation. Die Gesamtaussagekraft der Modelle war eher tief bis moderat. Mit 51% wurde die höchste Aussagekraft beim Model SSC & CCC erreicht. Die durch das Modell nicht erklärte Variation in den Fruchtfolgen lässt sich teilweise mit dem stark variierenden Düngermanagement in den verschiedenen Kulturen begründen. Räumlich explizite Fruchtfolgen haben nicht nur eine örtliche sondern auch eine zeitliche Komponente, die das Verständnis für Nährstoffflüsse in der stadtnahen Landwirtschaft verbessert hat.

Bio-physikalische und sozio-ökonomische Prozesse können zu räumlicher Fragmentierung von landwirtschaftlichen Nutzflächen führen. Fernerkundliche Methoden sind ein effizientes Mittel, um eine fragmentierte Landnutzung zu erfassen. Basierend auf räumlich hoch aufgelösten Quickbird Satellitendaten wurde die Anwendbarkeit der objektbasierten Bildanalyse für die Landnutzungsklassifikation einer stadtnahen Kommune in Hanoi evaluiert. Eine genaue Segmentierung der Form und Grösse eines Objekts verbessert die Klassifikation mit spektralen, texturalen, morphologischen und topologischen Anwendungen. Ein erster qualitativer, visueller Vergleich der Klassifikation bestätigte die erfolgreiche Lokalisierung und Identifikation der meisten Landnutzungsklassen. Die quantitative Beurteilung ergab jedoch eine Gesamtgenauigkeit von nur 67% und einen Kappa-Koeffizienten von 0.61. Eine objektbasierte Klassifikation von räumlich hoch aufgelösten Satellitendaten bietet einen vielversprechenden Ansatz für die Landnutzungsanalyse auf der Ebene eines Dorfes. Die Diversität in der Landnutzung und die Abgrenzung von Feldern bleiben in Bezug auf räumlich erheblich grössere Datensets allerdings eine Herausforderung.

Eine genaue Abgrenzung von Feldern ist eine wichtige Voraussetzung für die erfolgreiche Klassifikation von landwirtschaftlichen Kulturen mit fernerkundlichen Methoden. Auf der Basis von räumlich hoch aufgelösten Quickbird Satellitendaten wurde eine Methode zur Klassifikation von stark diversifizierter, stadtnaher Landwirtschaft auf Sub-Kommunen- und Kommunne-Ebene (7 km^2) entwickelt und getestet. Um die Abgrenzung von Feldern zu evaluieren, wurde eine objektbasierte und eine feldbasierte Segmentation und Klassifikation mit einer manuellen Klassifikation qualitativ und quantitativ verglichen. Die Evaluation auf Sub-Kommunen-Ebene resultierte im feldbasierten Verfahren in einer Gesamtgenauigkeit von 84 % und einem Kappa-Koeffizienten von 0.77.Das objektbasierte Verfahren erzielte jedoch nur eine Gesamtgenauigkeit von 56–60% und einen Kappa-Koeffizienten von 0.37–0.42. Das feldbasierte Verfahren führte somit zu besseren Resultaten und wurde zur Landnutzungsklassierung auf kommunaler Ebene verwendet. Die Gesamtgenauigkeit erreichte 83% und der Kappa-Koeffizient 0.7. In kleinräumlichen, diversifizierten landwirtschaftlichen Produktionssystemen, wie sie in stadtnahen Gebieten auftreten, erzielt eine feldbasierte Segmentation und Klassifikation noch immer die besseren Resultate.

Verfügbare Methoden und Arbeitsinstrumente zur Erfassung von Ressourcenflüssen in Städten ermöglichen einen guten Überblick über Prozesse, Massenflüsse und deren Interaktionen. Viele dieser Arbeitsinstrumente lassen jedoch die wichtige räumliche Komponente ausser Acht oder beziehen diese nicht genügend weit mit ein. Die im Schlusskapitel entwickelte Methode basiert auf den Modulen Farmsystem-Analyse, GIS und Fernerkundung. Dabei werden vier analytische Verfahren zur Untersuchung von räumlichen und zeitlichen Nährstoffflüssen vorgeschlagen: (i) Analyse der Landnutzung I, (ii) Analyse von Fruchtfolgen, (iii) Analyse von Nährstoffflüssen und (iv) Analyse der Landnutzung II. Die Resultate der einzelnen Verfahren werden dann für die Modellierung von räumlich expliziten Fruchtfolgen und den damit verbundenen Nährstoffflüssen verwendet. Die neugewonnenen Daten können für ein Umweltmonitoring eingesetzt werden und bilden eine Basis für die Entwicklung von räumlich und zeitlich expliziten Szenarien zur Wiederverwendung von organischen Abfalldüngern in der stadtnahen Landwirtschaft.

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Chapter 1

Introduction

1 Background

In 2008, more than half of the human population (3.3 billion people) lived in urban areas. By 2030, this figure is expected to rise to almost 5 billion. In the 20th century, the urban population grew from 220 million to 2.8 billion. However, the next few decades will see an unprecedented increase in urban growth in the developing world. Particularly in Africa and Asia, the urban population will double between 2000 and 2030. By then, the towns and cities of the developing world will make up 80% of urban humanity (UNFPA, 2007). This development is mainly caused by the natural increase in population and rural-to-urban migration (Boadi et al., 2005). The latter is seen as a result of the deteriorating rural environment and the hope for better livelihood opportunities in urban areas (Boadi et al., 2005). Especially economic motives are reported to drive people to migrate (Grant, 1995; Wu and Zhou, 1996).

Rapid urbanisation raises the spatial challenge of providing sufficient food for an agglomerating population. When considering the predicted population growth, it becomes apparent that significant efforts will be necessary to ensure urban food security in the next few decades. However, a large fraction of products imported to the urban areas to feed the urban population constitutes a so-called ‘urban nutrient sink’ (Alberti, 2005; Belevi, 2000; Drechsel et al., 2007; Montangero et al., 2007; Newcombe and Nichols, 1979; Wernick et al., 1998). Particularly in developing countries, much of these nutrients are lost since they are discharged into waterways. In the case of Bangkok, more than 90% of 26 000 t of nitrogen entering the city annually are lost through discharge to waterbodies (Færge et al., 2001). Thereby, households play a key role in transforming the goods entering the city in so-called ‘waste products’. Belevi (2000) estimated that households in the city of Kumasi, Ghana, are responsible for about 87% of nitrogen and 82% of phosphorus emissions to groundwater and surface waters, and 90% of nitrogen and 97% of phosphorus emissions to the soil. Furthermore, households also contribute 58% of nitrogen and 34% of phosphorus fluxes to the landfill.

In urban areas of developing countries the fraction of municipal solid waste collected is typically less than 50%, notwithstanding the fraction disposed of inappropriately (Birley and Lock, 1999; Schertenleib et al., 2004). Organic waste recycling (e.g. composting) is minimal or nonexistent in cities where the bulk of the waste ends up on streets, in drains or on uncontrolled dumps (Drechsel et al., 2007). Little consideration is given to the high fraction of organic waste (50–70%) (Allison et al., 1998) and its agricultural recycling potential. The term ‘waste’ is associated with a useless product to be disposed of, irrespective of its potential economic value. To enhance agricultural sustainability and thus ensure long-term food supply to cities, the former urban-rural links must be reintroduced (Magdoff et al., 1997; Smit et al., 1996).

2 Rationale

2.1 Urban and peri-urban agriculture and its potential for organic waste reuse

Urban agriculture has a very long history. People settled down where soils were especially fertile and water was abundant. For a long time, transport was limited and the rural hinterland was not entirely safe from enemies. Agriculture within the walls or close to the city was safer and distribution of products required less time and energy. Urban agriculture can be defined as the production, processing and distribution of a diversity of food products (e.g. vegetables and animal products) and non-food products (e.g. ornamental plants) within (intra-urban) or at the fringe (peri-urban) of an urban area (modified after Belevi and Baumgartner, (2003)).

Recent developments in urbanisation are shedding a new light on urban agriculture as a livelihood strategy for urban dwellers. Food security and income generation are the main driving forces to engage in urban agriculture. Surveys have revealed that urban farming provides 90% of the vegetables consumed in Dar es Salaam, 65–70% in Dakar and 60% in Shanghai (Nugent, 2000). Urban agriculture is also important in the fields of public health and sustainable resource management. The latter implies a more efficient use of resources, including a reduction and reuse of waste flows whenever possible. Closing the nutrient loop in the urban environment by reusing the so-called waste products as fertilisers and soil conditioners in urban agriculture is an alternative to the prevalent open-loop and linear urban systems (Nelson, 1996; Otterpohl et al., 1997; Schertenleib et al., 2004; Smit et al., 1996).

2.2 Soil fertility aspects in the developing world

Nutrients in harvested goods exported to urban areas exacerbates the problem of soil nutrient mining and leads to soil fertility decline and degradation in crop production areas (Drechsel et al., 2007; Drechsel and Kunze, 2001; Vlek et al., 1997). Therefore, to attain long-term agricultural productivity, soil degradation has to be halted and reversed. Soil fertility decline is a key factor in soil degradation and is strongly linked to the reduction of crop yields (Syers, 1997). In many parts of sub-Sahara Africa, for example, soil fertility decline is reported to be the main factor limiting crop production (Sanchez et al., 2003). Processes of nutrient depletion and soil degradation root in the underlying parent material, geomorphology and land use practices (Smaling et al., 1997). Soil fertility decline is primarily associated with the depletion of organic matter and plant nutrients. Though the turnover rate of organic matter may be higher in the tropics than in temperate regions, organic matter per se is essentially the same. Soil organic matter levels are closely related to above and below ground inputs. Where application of adequate amounts of organic material is missing and cultivation is continuous, soil organic matter depletes gradually. Thus, a guiding principle in developing agricultural management practices is to maintain the quantity and quality of soil organic matter (Syers, 1997). However, livelihood constraints force farmers to focus on the forthcoming season to maximise their net return from crop and/or animal production. Therefore, crop production progresses often at the expense of sustainable land use. Long-term processes, i.e. decrease in soil nutrient stocks, receive little attention as visibility is less apparent (Stoorvogel et al., 1993; Van den Bosch et al., 1998b).

Due to an increasing, mainly urban population and demand for more food, nutrient requirements for crop production in the developing world will double between 1990 and 2020. Furthermore, as unsustainable land use is likely to continue, these nutrient requirements will have to be increasingly met by the mere soil reserves. Furthermore, as arable land is limited, focus on a more efficient use of nutrient inputs and their management will gain importance (Vlek et al., 1997). Thereby, all possible sources of nutrients should be considered, i.e. those supplied by soil organic matter, animal excreta and manure, human waste and mineral fertilisers (Goulding et al., 2008).

Closing the nutrient cycle at an inter-regional level is associated with considerable collection, treatment and transport costs to the farms (Vlek et al., 1997). The high transport costs are probably the main cause for the limited success of organic waste recycling to rural areas. Yet, due to the much shorter distances, peri-urban agriculture – agriculture in the urban-rural interface – could play a key role as a recipient of organic solid and liquid waste from inner-urban areas. It can also help to overcome the waste problem, save limited resources and contribute to food security (Brock, 1999; Drechsel and Kunze, 2001; Dulac, 2001; Schertenleib et al., 2004; Strauss, 2001).

2.2 Methods and tools for enhanced decision-making

Rapid urbanisation processes lead to uncontrolled peri-urban land development with complex urban structures marked by predominantly horizontal expansion (Kombe, 2005). Survey and integration of agricultural land and new urban use require tools going beyond traditional planning approaches (Drescher, 2000). With regard to recycling and reuse of urban organic waste in peri-urban agriculture, such a planning tool should be flexible enough to (a) capture spatial diversity (or heterogeneity) in peri-urban agriculture, (b) identify different farming systems and associated patterns, (c) link material and nutrient flows to cultivated crops, and (d) assess nutrient flows and budgets over spatial and temporal scales at village and communal level. As regards local organic waste generation (e.g. animal manure and human waste), the tool should then allow to develop waste reuse options for the status quo and future scenarios. Furthermore, such a tool should allow frequent updating without repeated tedious field surveying.

3 Objectives

The main objective is the development of a methodology to assess nutrient flows and budgets at farm, village and communal level of peri-urban agricultural production systems by taking into account the spatial and temporal variability of crop and nutrient management. The methodology should be discussed in the context of recycling and reuse of organic waste products in peri-urban agriculture. The following specific objectives were formulated:

1. To explore and describe driving factors responsible for patterns in land use of peri-urban agricultural production systems at farm and village level.
2. To assess nutrient flows and budgets linked to patterns of land use in peri-urban agricultural production systems at farm and village level.
3. To investigate the potential of remote sensing and geographical information systems for land cover/land use assessment at field, village and communal level of peri-urban agricultural production systems.
4. To explore and describe the feasibility of upscaling nutrient flows and budgets from field to village and communal level as a function of the outputs of the specific objectives 1 to 3.

4 Methodological approach

By combining the advantages of different methods, such as farming systems analysis, nutrient budget estimations, remote sensing and geographical information systems, a methodology was developed allowing to assess nutrient flows and budgets at farm, village and communal level of peri-urban agricultural production systems.

4.1 Research in agricultural systems

Agricultural systems consist of different interdependent components. The components operate within a defined system boundary allowing to achieve a specified agricultural objective (McConnell and Dillon, 1997). The system components – representing a set of related subsystems – can be allocated to a system hierarchy. For instance, soil microorganisms can be regarded as subsystem of the soil system. The soil system can be referred to as a subsystem of the crop production system and regarded as a subsystem of the farm system. Systems can thus be classified according to the characteristics of sub-systems, i.e. type of rotation, intensity of rotation, cropping pattern and livestock activities, the implements used for cultivation or degree of commercialisation (Ruthenberg, 1980).

Farming systems analysis presents a tool to investigate farm management practices allowing to develop new methods for agricultural research. Various approaches are available to involve views and perspectives of local farmers in systems analysis. Lynam et al. (2007) classified these approaches into three groups: (1) diagnostic and informing methods that extract knowledge, values or preferences from a target group, (2) co-learning methods in which the perspectives of all groups change as a result of the process and (3) co-management methods in which all the actors involved are learning. The first two methods are used to understand local issues more effectively and include them in decision-making processes, while in the third method, the actors themselves participate in the decision-making process. For instance, rapid rural appraisal (RRA) and participatory rural appraisal (PRA) are two innovative methods for diagnostic surveys in agricultural, rural development research (Chambers, 1994), which can be associated with the first group 'diagnostic and informing methods'. Selection of the most suitable approach depends much on the research questions, objectives and often on the required logistics. In this thesis, farming systems analysis by diagnostic and informative methods was used (e.g. transect walks, surveys, repeated visits, and discussions with farmers) to explore and describe patterns of crop and nutrient management within diverse, small-scale peri-urban farming systems.

4.2 Nutrient management

Crop and nutrient management are strongly interrelated and generally investigated together using nutrient budgets and balances. In Europe, nutrient budgets and balances are widely adopted tools for developing more sustainable agricultural systems (Craswell and Lefroy, 2001; Goodlass et al., 2003; Menzi and Gerber, 2006; Oborn et al., 2003; Scoones and Toulmin, 1998). At national level, nutrient budgets and balances have mainly been implemented to meet environmental targets for nutrient management in agriculture (Oborn et al., 2003). Nutrient budgets and balances can thus greatly contribute to selecting the appropriate policies, strategies and interventions (Scoones and Toulmin, 1998). The basic principle of nutrient budgets and balances is to identify the nutrient inputs and outputs of a bounded system and its various sub-compartments. Quantification of these nutrient inputs and outputs allows to assess nutrient management on a farm in terms of budgets and balances (Jassen, 1999; Oborn et al., 2003).

Three different types of nutrient budgets can be distinguished within the context of an agro-ecosystem. Each type of budget has its benefits and drawbacks (Oborn et al., 2003; Oenema et al., 2003):

- The farm-gate budget or black box approach records the amounts of nutrient in all kinds of products entering and leaving the farm via the farm-gate.
- Soil-surface budget records all the nutrients entering the soil via the surface and leaving the soil via crop uptake.
- Soil-system budget records all nutrient inputs and outputs, including nutrient gains and losses within and from the soil. This approach is often used in research studies to identify nutrient surpluses.

Most nutrient budget studies are calculated at soil-surface (Scoones and Toulmin, 1998) or at farm-gate level (Sacco et al., 2003). At soil-surface level, different cropping units are distinguished as a function of crop type, landscape position or management intensity.

Nutrient flows of nitrogen, phosphorus and potassium are usually assessed, while micronutrients and organic matter are ignored. Nutrient budgets are mainly based on average estimates. However, since the farmers' strategy is to develop and make use of diversity, this represents a fundamental difference in approach (Scoones and Toulmin, 1998). Usefulness and reliability of a budget strongly depend on its completeness (Schroder et al., 2003). The different confidence intervals of the data sources are thus a critical issue when calculating nutrient budgets. As long as data can easily be measured or derived from literature (e.g. flows of material such as fertiliser, manure, crop residues, and harvested grains), the error will remain at an acceptable range. However, for other data, such as for volatilisation, deposition or denitrification, an assessment is more difficult. In such cases, researchers often refer to literature estimates without validating these in the study area. Simple, accurate and fully objective measurements of nutrient flows in farming systems are almost impossible. Nutrient budgets are thus known to be 'inconstant', which may also be considered as a lack of certainty (Oenema et al., 2003). Different sources of bias and error prevail as regards personnel, sampling, measurement, data manipulation, and fraud (Oenema and Heinen, 1999).

Aside from the general wish for completeness in terms of nutrient budgets and awareness of sources of bias and error, the prevailing opinion is that models should be kept as simple as possible, but detailed enough to capture the major processes influencing the behaviour of the system with regard to the research question raised (De Wit, 1968; Tittonell, 2008).

Description details do not definitely enhance the explanatory capacity of the model (Stoorvogel and Antle, 2007). Excessive details in terms of numbers of processes and levels of integration will increase uncertainty in model parameters and reduce output quality. Therefore, partial nutrient budgets or even specific nutrient flows may reduce complexity and uncertainty and, thus, be more suited to explain the nutrient management process in diverse, small-scale agricultural production systems.

However, bias and error sources are also associated with nutrient flows at various spatial scales (e.g. plant, plot, farm, village, district, country or continent). The hierarchy of the scales is not the same for all processes involved (Schlecht and Hiernaux, 2004). Nutrient flows underlie spatial and temporal variations, which are important when assessing nutrient budgets (Craswell and Lefroy, 2001). Nutrient flows are mainly influenced by effects of a spatial, temporal and management scale (Schlecht and Hiernaux, 2004; Scoones and Toulmin, 1998). Thus, farm-scale data can only be extrapolated to a region if the studied farms are representative of all other farms in the region (Sacco et al., 2003). Spatial problems may be addressed by using geographical information systems (GIS) allowing spatial data from diverse sources (different spatial scales) to be combined and presented as different interdependent data layers (Schlecht and Hiernaux, 2004).

4.3 GIS and remote sensing

The GIS system is designed to capture, store, update, manipulate, analyse, and display geographic information. It is typically used to represent maps as data layers for further studies and analyses (ESRI, 2004). GIS has become a leading tool for developing applications in urban and regional analysis (Tulloch et al., 2003; Zhang et al., 2004), and also in agricultural research and planning (Ahmadi and Merkley, 2009; Gerber et al., 2005; Gibson et al., 2007; Tornquist et al., 2009; Tulloch et al., 2003). Besides, remote sensing (RS) provides additional site-specific information for land use mapping (Thomson and Hardin, 2000). Space or airborne sensors deliver high (5–30 m spatial resolution) to very high (0.6–4 m spatial resolution) image data for land use analysis. Image analysis was commonly based on pixel classification. Single pixels can thus be labelled to different land cover land use categories. Classification results are reported to be satisfactory with parcel sizes of 30 m or larger (De Kok et al., 2002). However, very high spatial resolution data lead to so-called ‘salt and pepper' results due to high spatial frequency within usually homogeneous land categories. The combined use of GIS and RS has led to the development of object-based classification methods. In object-based classification, pixels with similar spectral characteristics are first grouped by a segmentation procedure. The resulting objects or segments are then labelled to specific land use categories (Benz et al., 2004; Blaschke et al., 2000; De Kok et al., 2002; Schiewe and Tufte, 2002). Object-based classification is known for its potential to analyse diverse, small-structured environments (Blaschke et al., 2002). Compared to the traditional methods used in farming system analysis, GIS an RS allow to scale up land use from the field to the farm, the village, the commune or even the district. Thus, uncertainty related to spatial crop management (i.e. land use) can be reduced considerably.

5 Outline of thesis

The chapters of this thesis have been arranged according to the specific objectives (section 4). Chapter 2 explores and describes factors influencing land use of a diverse, small-scale agricultural production system in a peri-urban commune of Hanoi, Vietnam. Spatial and temporal aspects of land use are thus considered, and models developed for analysis and prediction. In Chapter 3, nutrient flows associated with dominant land use patterns are assessed. Nitrogen flows serve as indicator for nutrient management and are explained by means of statistical models. Though, chapters 2 and 3 provide important spatial and temporal aspects of nutrient flows, remote sensing and geographical information systems can add further valuable information to reduce uncertainty related to spatially explicit land use. Chapter 4 investigates the potential of remote sensing and geographical information systems for land cover/land use assessment at field, village and communal level. Special emphasis was placed on object-based fuzzy classification reported to have considerable advantages over traditional, pixel-based approaches in diverse, small-scale production systems. Chapter 4.1 focuses on object-based classification at sub-communal level. Chapter 4.2 evaluates object-based versus per-field classification for upscaling land use at communal level. Finally, chapter 5 summarises aspects of chapters 1 to 4. It explores and describes the feasibility of upscaling nutrient flows and budgets from field to village and communal level. This chapter reflects on the organic waste recycling and reuse methodology in peri-urban agriculture and also provides a brief outlook. Chapters 2–4 summarise published work or papers under review for publication.

Chapter 2

Exploring spatially explicit crop rotation models for peri-urban agricultural production systems – A case study [*]

[*] This chapter is based on:
Forster D., Amini M., Menzi, H., Vu Dinh, T., Lennartz, B., 2009. Exploring spatially explicit crop rotation models for peri-urban agricultural production systems - A case study. Agricultural System, submitted.

Abstract

Abundant use of fertilisers leads to soil and water pollution. Conversely, inadequate use of fertilisers negatively affects soil fertility and consequently agricultural production. Site-specific nutrient management (SSNM) is suggested to sustainably combat fertiliser surpluses and deficits. Site-specific analysis of agricultural land use is an important step in SSNM. However, the available models are usually based on raster data retrieved from satellite images and processed in a geographic information system (GIS). The satellite images, yielded from remote sensing data, are not only subject to tasking orders, but the number of images required is high and the socio-economic factors are difficult to obtain. Analysis of crop rotations explored during farming systems surveys can be regarded as an alternative. Environmental and social rules and regulations play an important role in land use practices and influence combination as well as crop rotation frequency and sequence. Information on the presence/absence of specific crop rotation patterns in the spatial context could add an important temporal component to site-specific crop and fertiliser management. This study aimed at identifying driving forces for specific crop rotations occurring in 'space' in a peri-urban commune of Hanoi, Vietnam. Statistical models relating proximate causes to specific crop rotations were developed and tested with an extensive set of explanatory variables using logistic regression procedures. The following three different crop rotations were evaluated: staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop based (CCC). Results revealed that distance and perceived soil fertility best explain occurrence of certain crop rotations. Models based on path or Euclidian distance performed better than those using built-up buffer distances. Euclidian distance and perceived soil fertility resulted in 79% correct predictions. When tested for SSF, the area under curve (AUC) value – an indicator for the overall performance of the model – amounted to 0.84. For the SSC and CCC rotations, the model reached 72 and 90% correct predictions, for AUC the values obtained were lower (0.74 and 0.75). This study identified driving forces for spatially explicit crop rotations to predict agricultural land use patterns and changes over space and time. Future studies should centre on the transferability of the derived models to other regions with a comparable environmental and socio-economic background.

Keywords: crop rotation, cropping pattern, land cover/land use, logistic regression, Vietnam, Hanoi

1 Introduction

Abundant use of fertiliser leads to soil and water pollution. On the contrary, inadequate use of fertiliser, will over mid or long-term affect soil fertility, agricultural production and eventually food security. Especially tropical and subtropical regions are confronted with serious soil fertility degradation inevitably threatening food security. Site-specific nutrient management (SSNM) is suggested to sustainably combat fertiliser surpluses and/or deficits (Dobermann and Cassman, 2002; Dobermann and White, 1999; Hu et al., 2007; Kahabka et al., 2004; Khurana et al., 2007; McCormick et al., 2009; Pampolino et al., 2007; Plant, 2001; Rüth and Lennartz, 2008; Vanlauwe et al., 2006). SSNM, which is the dynamic, field-specific management of nutrients during particular cropping seasons, is applied to adjust supply and demand according to differences in cycling through soil-plant systems (Buresh, 2007; Dobermann and White, 1999; Pampolino et al., 2007). SSNM, also known as precision farming, is part of site-specific crop management (SSCM). SSCM can be regarded as matching resource application and agronomic practices with soil attributes and crop requirements proportional to their spatial and temporal variation (Dobermann and White, 1999; Mzuku et al., 2005).

Site-specific analysis of agricultural land use is an important step in SSNM. Basically two different approaches are applied to study agricultural land use: (i) by analysing raster data derived from air borne or space borne sensor (e.g. orthophoto or satellite images) and (ii) by empirical analysis of cropping patterns (i.e. crop rotations) obtained from farming system surveys. Raster data analysis is usually performed by remote sensing (RS) and geographic information system (GIS). Based on explanatory variables, logistic regression or fuzzy logic models predict the likelihood of grid cells allocated to specific land cover/land use classes. Comparison of data time series (e.g. multi-temporal and trajectory land cover/land use analysis) allows to develop models over time and improves the understanding of proximate causes of change (Serneels and Lambin, 2001). So far, mainly high resolution satellite data (e.g. Landsat TM, ETM or Spot) of a spatial resolution ranging between 15–30 m pixel size was used for multi-temporal and trajectory analysis. For instance, Martinez-Casasnovas et al. (2005) used multi-temporal image data (e.g. Landsat TM and ETM) to analyse spatial and temporal cropping patterns and to retrieve site-specific crop rotations. High-resolution satellite data provides good information on large fields spreading over several hectares. However, small-scale agricultural production systems ranging between 50 and 1000 m^2 field size require very high spatial resolution satellite data (0.5–5 m pixel size) as provided by Quickbird, Ikonos or Spot 5 HRG. Yet, these images are subject to tasking orders, which may or may not be executed (Forster et al., 2009c). Thus, investigation of agricultural land use trajectories by remote sensing is limited on account of the large number of satellite images required. Additionally, socio-economic factors affecting agricultural land use are extremely difficult or impossible to obtain from remote sensing data.

Empirical analysis of agricultural land use patterns by crop rotations is considered as an alternative to pixel based multi-temporal or trajectory analysis, especially in diverse, small-scale agricultural production systems. Crop rotations at field level aim at achieving sustained high crop production while maintaining natural resources over time (Bockstaller et al., 1997; Dogliotti et al., 2003; Joannon et al., 2008). The physical environment (Joannon et al., 2008) as well as social rules and regulations (Balent and Stafford-Smith, 1993) play a key role in allocating crop rotations. For instance, soil, water, topography, and field location strongly influence combination and sequence of crops in rotation. The potential yield of a crop depends on quantity and type of inputs supplied. Environment and land management also significantly influence the supply of inputs and affect physical, chemical and biological soil fertility. Crop combination, frequency, sequence, and activities during crop-free periods mainly determine these effects and cause rather fixed patterns in production source requirements: labour, water, machinery, storage facility, and cash flow (Dogliotti et al., 2003; Joannon et al., 2008; Rounsevell et al., 2003; Struik and Bonciarelli, 1997). Therefore, where environmental factors tend to spatially cluster, patterns in crop rotation and production source requirements are expected. As a result, strong similarities in crop rotation among individual farms and landscapes can be observed (Mignolet et al., 2007). A better understanding of the factors promoting crop rotations could enhance site-specific crop and nutrient management while adding a further important temporal component.

This study thus aimed at determining factors allowing to predict the likelihood of a specific crop rotation in a peri-urban commune of Hanoi, Vietnam. The following assumptions were made: (i) distance between homestead and specific field site, distance from closest road to field site, soil fertility, water availability 1st, 2nd and 3rd season, relative elevation topography, plot size, and farm livestock number are key factors promoting crop rotations, (ii) built-up buffer distance best explains appearance of a crop rotation compared to Euclidian or path distance and (iii) crop rotations with an increased proportion of staple crops are more likely to be found on remote fields while rotations with cash crops tend to be on fields close to the farm homestead.

2 Materials and Methods

2.1 Study environment

Research was conducted in the district of Dong Anh (21° 8′ 14′′ N; 105° 49′ 44′′ E) about 6 km north of the capital Hanoi, Vietnam. The commune of Bac Hong was selected for its divers production system. Land is distributed around a densely populated area, where agriculture is still the main source of income. The commune covers 7.2 km^2 of flat land, 5.1 km^2 of which are allocated to agricultural production. Elevation ranges between 8 to 12 m above sea level. The soils of the study region are mainly Plinthic Acrisols or Hapli Plinthic Acrisols according to FAO-UNESCO classification (Nguyen et al., 2004). The soils are generally light in texture, varying between loamy sand to light loam, with low organic matter content (>1.26%) and pH ranging from slightly acid to neutral. The irrigation and drainage system covers the entire cropping area in all three villages. During the first two growing seasons (mid-February to mid-June, mid-June to mid-October), excess water is drained. However, in the third growing season (October to February), irrigation is necessary. Mixed farming is common practice, including crop and livestock production. Staple crops, such as rice paddy (*Oryza s.* L.), sweet potato (*Ipomoea batatas* L), as well as cash crops like maize (*Zea maize* L.), are the main crops planted during the first and the second season. Since maize and other cash crops, such as vegetables, are grown on a reduced land area during the third season (Table 1), much of the land remains fallow.

2.2 Selection of farms and fields

Three villages (Thuy Ha, Thuong Phuc and Ben Chung) of the six villages of the Bac Hong commune were selected for the study. The villages' leading committees were asked to list 25 farmers representing the farming community. To spatially cover the entire region, 12 farmers from Thuy Ha and Thuong Phuc and ten farmers from the Ben Chung village were selected (Fig. 1). The farms were about 0.2 ha in size and the fields were generally small ranging from

79 to 862 m^2 in size and averaging 305 m^2. With five to seven fields per farm, a total of about 201 fields were selected for the study.

Table 1. Crops grown in major (X) and minor (x) seasons in the Bac Hong commune, Hanoi province.

	Season[1)]		
	1st	2nd	3rd
Annual crops			
Rice paddy (*Oryza s.* L)	X	X	-
Maize (*Zea maize* L)	x	x	X
Sweet potato (*Ipomoea batatas* L)	x	x	X
Peanut (*Arachis hypogaea* L)	x	x	X
Soybean (*Glycine max* L)	x	x	X
Cabbage (*Brassica oleraceae var. capitata*)	x	x	X
Kohlrabi (*B. o. var. gongylodes*)	x	x	X
Broccoli (*B. o. var. botrytis*)	x	x	X
Pak-choi (*B. rapa spp. chinensis*)	x	x	X
Tomato (*Lycopersicon esc. var. esculentum*)	x	x	X
Eggplant (*Solanum melongena*	x	x	X
Cucumber (*Cucumis sativus* L.)	x	x	X
Pumpkin (*Cucurbita maxima*)	x	x	X
Perennial crops	X	X	X
Peach trees (*Prunus* sp.)	X	X	X
Star fruit (*Averrhoa carambola* L.)	X	X	X
Longan (*Dimocarpus longan*)	X	X	X
Lychee (*Litchi chinensis*)	X	X	X
Mango (*Mangifera domestica* L.)	X	X	X
Sapodilla (*Manilkara zapota* L.)	X	X	X
Banana (*Musa* sp.)	X	X	X

[1)] 1st season: mid-February to mid-June, 2nd season: mid-June to mid-October, 3rd season: mid-October to mid-February.

2.3 General field/plot typology and data collection

The intensive and continuous cropping system required a well-delineated field/plot typology and advanced data management. As for other rice growing areas, farmers' fields were usually demarcated by permanent bunds, separating each field from neighbouring fields and avoiding water drainage. However, especially during the third growing season, farmers frequently subdivided their fields into smaller plots. Therefore, each field consisted of possibly one or more plots, which could be adjusted in size. As plot structures were of temporary nature, they had a specific start and end usually coinciding with the start and end of the cropping season.

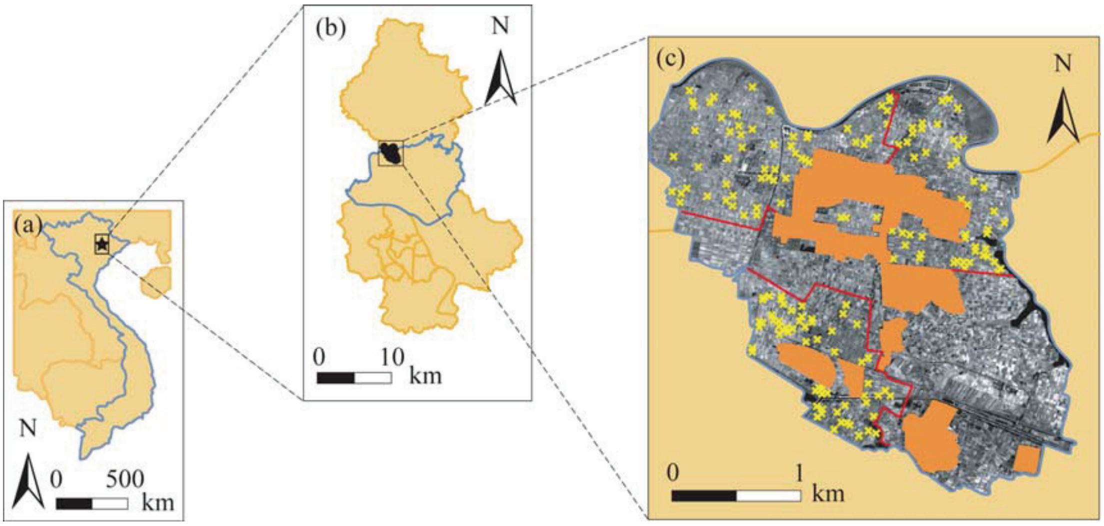


Fig. 1. The study area of Vietnam (a), Hanoi province and Dong Anh district (b), the commune of Bac Hong with built-up area and farmers' fields (c).

To account for agricultural diversity, data collection used semi-structured interview techniques, a tailored system database (MSAccess®) and a differential GPS system (Leica GS20®). Instead of collecting simple field centre points, the recorded plot shape allowed to assess the field/plot size. Post-processing of GPS field data (i.e. differential correction) with Leica GIS DataPro® increased positioning to sub-meter accuracy. Interviews were conducted on all 34 farms. Together with the farmer, the team visited each of farmers' fields along a transect walk. The environmental conditions (e.g. soil quality) and management practice of each field were thus discussed and complemented by a farm map. Homestead and fields were recorded by GPS to estimate different distance parameters. The survey was conducted over a period of two consecutive years (2005/2006) and during the third growing season (Oct. 2005–Jan. 2006 and Oct. 2006–Jan. 2007).

2.4 Variables influencing cropping pattern

Farmer's choice and management of crop rotations are assumed to be of environmental and socio-economic nature. This study investigated the effect of distance, field size, soil fertility, water availability, topography, and livestock on crop rotation (Table 2).

Distance was calculated in three different ways; (i) path distance, (ii) Euclidian distance and (iii) buffer distance. Path distance is the distance in meters from the homestead to the field under investigation. Path algorithm, i.e. selection of the shortest path on a road-path infrastructure network, was used to calculate path distance. Euclidian distance, which is the direct distance between homestead and field, was calculated with the corresponding function in the GIS software. However, buffer distance, which is the distance from the border of the built up area to the farmer's field, was implemented by assigning distance intervals to the fields by means of the multiple buffer function in the GIS. To compare path and Euclidian distance to buffer distance, path and Euclidian distance was also arranged in distance intervals. Similar to buffer distance, also road buffers were implemented. The distance from the nearest road to the respective field was assigned by means of the multiple buffer function.

Field size was recorded by a differential GPS system as described in section 2.3. Soil fertility was evaluated as perceived by the farmer. The perceived soil fertility of each field was discussed by comparing it with other fields during the transect walk. The farmer had the choice to select one of three classes (0 = infertile, 1 = medium, 2 = fertile soils). Water availability was addressed for each growing season and included water supplied by rainfall and by the irrigation system. Farmers were asked to classify water availability in two categories: 0 indicated no water availability and 1 that water was available in sufficient quantity.

Relative elevation topography is a locally used term to evaluate the elevation of a field compared to neighbouring fields. In a cascading system, the relative elevation topography indicates whether a field mainly receives water from neighbouring fields (sunken field), or directly from the irrigation channels (on top of the cascade). Together with the interviewer, the farmer classified his/her fields into three categories (0 = sunken, 1 = medium, 2 = high). The number of livestock was counted while visiting the homestead (survey 2005/2006). Average number of cattle, pigs and poultry was recorded and transferred into FAO's universal livestock units (FAO, 2003).

Table 2. Summary of explanatory variables used in cropping pattern analysis.

Variable name		Type	Unit
Dependant variables			
Crop rotation: SSF		Categorical	0 – 1
Crop rotation: CCC & SSC		Categorical	0 – 1
Crop rotation: CCC		Categorical	0 – 1
Crop rotation: SSC		Categorical	0 – 1
Independent variables			
Path distance, homestead – field		Continuous	Meter
Path interval (1)	0 – 200 m	Categorical	0 – 1
Path interval (2)	200 – 400 m	Categorical	0 – 1
Path interval (3)	400 – 600 m	Categorical	0 – 1
Path interval (4)	600 – 800 m	Categorical	0 – 1
Path interval (5)	800 – 1000 m	Categorical	0 – 1
Path interval (6)	1000 – 1200 m	Categorical	0 – 1
Path interval (7)	1200 – 1400 m	Categorical	0 – 1
Path interval (8)	>1400 m	Categorical	0 – 1
Euclidian distance, homestead – field		Continuous	Meter
Euclidian interval (1)	0 – 200 m	Categorical	0 – 1
Euclidian interval (2)	200 – 400 m	Categorical	0 – 1
Euclidian interval (3)	400 – 600 m	Categorical	0 – 1
Euclidian interval (4)	600 – 800 m	Categorical	0 – 1
Euclidian interval (5)	800 –1000 m	Categorical	0 – 1
Euclidian interval (6)	1000 –1200 m	Categorical	0 – 1
Euclidian interval (7)	>1200 m	Categorical	0 – 1
Buffer (1), built-up area – field	0 – 100 m	Categorical	0 – 1
Buffer (2)	100 – 200 m	Categorical	0 – 1
Buffer (3)	200 – 300 m	Categorical	0 – 1
Buffer (4)	300 – 400 m	Categorical	0 – 1
Buffer (5)	400 – 500 m	Categorical	0 – 1
Buffer (6)	500 – 600 m	Categorical	0 – 1
Buffer (7)	600 – 700 m	Categorical	0 – 1
Buffer (8)	700 – 800 m	Categorical	0 – 1
Buffer (9)	> 800 m	Categorical	0 – 1
Road buffer (1), road – field	0 – 25 m	Categorical	0 – 1
Road buffer (2)	25 – 50 m	Categorical	0 – 1
Road buffer (3)	50 – 75 m	Categorical	0 – 1
Road buffer (4)	75 – 100 m	Categorical	0 – 1
Soil fertility (low)		Categorical	0 – 1
Soil fertility (average)		Categorical	0 – 1
Soil fertility (high)		Categorical	0 – 1
Water availability during 1st season		Categorical	0 – 1
Water availability during 2nd season		Categorical	0 – 1
Water availability during 3rd season		Categorical	0 – 1

Table 2. (continued).

Relative elevation topography (low)	Categorical	0 – 1
Relative elevation topography (average)	Categorical	0 – 1
Relative elevation topography (high)	Categorical	0 – 1
Field size	Continuous	Meter sq.
Farm livestock number	Continuous	LU[1]
Cattle	Continuous	LU[1]
Pig	Continuous	LU[1]
Poultry	Continuous	LU[1]

[1] Livestock unit.

2.5 Data analysis

Exploratory data analysis was used to describe the environment of the Bac Hong commune and investigate patterns of agricultural land use over space and time. The logistic regression technique (Agresti, 2002; Hosmer and Lemeshow, 1989) was applied to develop spatially explicit crop rotation models. Logistic regression is a statistical technique to analyse the probability of a categorical dichotomous outcome, which is explained by a set of independent, continuous or categorical variables. It has been mentioned and used in various studies to predict or adopt agricultural land use and cultivation practices (Austin et al., 1998; Castella and Verburg, 2007; Neupane et al., 2002; Overmars and Verburg, 2006; Serneels and Lambin, 2001; Sheikh et al., 2003). A logistic regression with several independent variables (x_i) can be formulated as follows (Eq. 1):

$$P(Y) = \frac{1}{1 + \exp^{-(b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_n X_n + \varepsilon_i)}} \qquad (1)$$

where b_0 is the intercept, b_i the regression coefficient for independent variable x_i, and ε_i the error term.

Maximum likelihood estimates, standard error (S.E.), Wald statistic (χ^2), and the odds ratio are used to verify model performance. A positive regression coefficient increases the likelihood of occurrence of an event, while a negative regression coefficient will reduce the likelihood of occurrence of that event. Additionally, the odds ratio can be used to ease model interpretation (Agresti, 2002; Hosmer and Lemeshow, 1989). The odds ratio is calculated by the probability of an event to occur divided by the probability of that event not to occur. It is an indication of change in odds due to a unit change in the independent variable. A value greater than 1 indicates an increase in the odds for an outcome to occur, whereas a value lower than 1 designates a decrease in the odds for an outcome to occur (Field, 2005). The goodness-of-fit was calculated for the respective models based on Nagelkerke's R^2_{N} (Nagelkerke, 1991). Although R^2_{N} can vary between 0 and 1, its value tends to be considerably lower than the R^2 used in the evaluation of linear regression models. Values between 0.2 and 0.4 can be considered as an extremely good model fit (Domencich and McFadden, 1975; Louviere et al., 2000).

Furthermore, the ROC (Receiver Operation Characteristics) of each model was computed for model comparison. The ROC curve displays sensitivity versus 1–specivicity for possible cutoffs from 0 to 1 (Agresti, 2002). Besides, the Area Under Curve (AUC), which is a combined measure of sensitivity and specificity, was estimated. It is a measure of the overall performance of a model and can be interpreted as the average value of sensitivity for all possible values of specificity. According to Pontius Jr and Schneider (2001), the AUC is calculated using the following integral trapezoidal rule (Eq. 2):

$$AUC = \sum_{i=1}^{n} \left[x_{i+1} - x_i\right] \left[y_i + y_{i+1} - y_i/2\right] \qquad (2)$$

where x_i and y_i represent sensitivity and 1-specificity for cutoff value i, respectively. The closer the AUC value gets to 1, the better the overall model performance. Conversely, if the AUC value equals 0.5, model prediction was not better than a random guess. In this study, SPSS® software package was used for statistical analysis.

3 Results and Discussion

3.1 Crop rotations

The number of cropping seasons per year varied in the commune (Fig. 2a). Two and three cropping seasons per year were more frequent on about 45% and 35% of the surveyed fields.

Other cropping seasons were less frequent and accounted for 20% of the fields. As rice paddy dominated the first and second cropping season, the crop rotation rice-rice-fallow was observed on 41% of the fields covering 2.8 ha or about 38% of the surveyed area (Fig. 2b). The rice-rice-vegetables and rice-rice-maize crop rotations were observed on 1 and 1.1 ha, corresponding to about 14% and 15% of the surveyed area. The crop rotations rice-rice-sweet potato, maize-maize-maize or maize-maize-vegetables were found on less than 1 ha. However, a considerable surveyed area (1.4 ha) was allocated to other crop combinations.

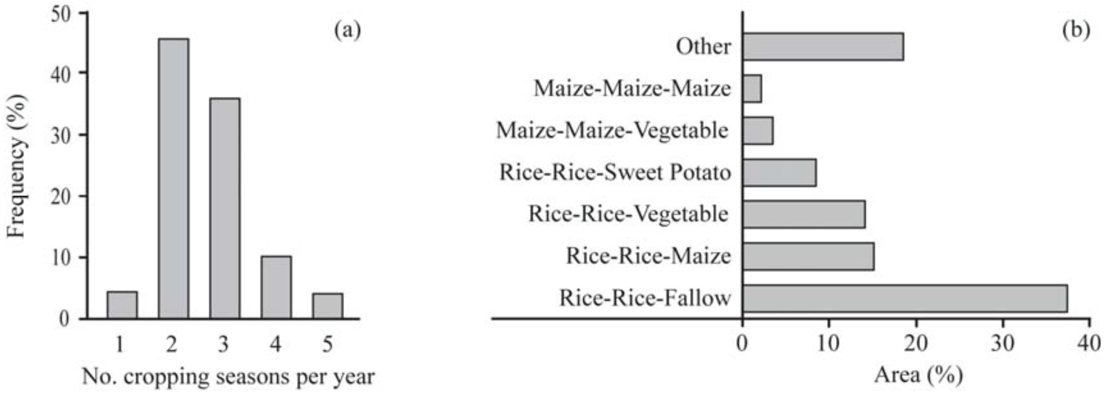


Fig. 2. Frequency of seasonal crop rotations (a) and proportion of different crop rotations in the commune of Bac Hong (b).

With every additional crop in rotation, the possibilities in recombination increased and rendered analysis of crop rotations a challenge. However, a simplified agricultural land use coding into fallow land, staple and cash crop allowed to explore all the survey data. Consequently, vegetable, maize and sweet potato were labelled as cash crops (C), rice as staple crop (S) and fallow land as F. Recombined crop rotations were labelled as SSF, SSC, CCC, accounting for 43, 27 and 12% of the surveyed fields. The remaining 18% were associated with other crop combinations.

3.2 Maximum likelihood estimates of staple crop-based crop rotation

For maximum likelihood estimates of staple crop-based rotations, the SSF rotation was evaluated against all other crop rotations. Descriptive statistics of independent variables used in the models are summarised in Table 3. Independent variables were also tested for multicollinearity; however, they were below the critical threshold value.

Table 3. Descriptive statistics of the independent variables used to assess copping patterns.

Variable name	Thuy Ha village (n = 75)		Thuong Phuc village (n = 77)		Ben Trung village (n = 49)		Commune (n = 201)	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Path interval (1)	0.09	0.03	0.09	0.03	0.00	0.00	0.07	0.02
Path interval (2)	0.05	0.03	0.26	0.05	0.02	0.02	0.12	0.02
Path interval (3)	0.07	0.03	0.42	0.06	0.33	0.07	0.26	0.03
Euclidian interval (1)	0.09	0.03	0.18	0.04	0.02	0.02	0.11	0.02
Euclidian interval (2)	0.13	0.04	0.57	0.06	0.33	0.07	0.35	0.03
Euclidian interval (3)	0.12	0.04	0.18	0.04	0.35	0.07	0.20	0.03
Euclidian interval (5)	0.21	0.05	0.01	0.01	0.10	0.04	0.11	0.02
Buffer (1)	0.15	0.04	0.25	0.05	0.20	0.06	0.20	0.03
Buffer (2)	0.19	0.05	0.27	0.05	0.35	0.07	0.26	0.03
Buffer (3)	0.11	0.04	0.30	0.05	0.14	0.05	0.19	0.03
Soil fertility (av.)	0.43	0.06	0.66	0.05	0.53	0.07	0.54	0.04
Soil fertility (high)	0.20	0.05	0.21	0.05	0.24	0.06	0.21	0.03

Three explanatory models named ‘Path Interval’, ‘Euclidian Interval’ and ‘Built-up Buffer’ (Table 4) were developed using the independent variables (Table 2). In all models, distance to the field and soil fertility were more significant ($P < 0.05$) and provided better results. Based on the calculated R^2_N, the Euclidian interval ($R^2_N = 0.45$) and path interval models ($R^2_N = 0.42$) provided a better explanation of SSF occurrence than the model based on built-up buffer ($R^2_N = 0.21$).

To further elucidate performance of the model, selected cutoff values from 0 to 1 were listed in a classification table for the SSF crop rotations (Table 5). The overall percentage of correctly classified fields ranged from 43 to 77% using the path interval model, from 43 to 79% for the Euclidian interval model and from 43 to 72% for the built-up buffer model. Thus, the path interval and Euclidian interval models performed better than the built-up buffer model. At a cutoff value of 0.5, false negative prediction was lowest in the path interval model and highest in the built-up buffer model. Conversely, false positive prediction was lowest in the built-up buffer model and highest in the path interval model. For instance, at a specificity and sensitivity level of 77% (model path interval), 20 of 201 fields were mistakenly classified as fields without SSF crop rotation, while in fact they had. Contrarily, in the same classification process, 26 of 201 fields were incorrectly classified as fields with SSF crop rotations.

Table 4. Maximum likelihood estimate for SSF crop rotation.

Variable		Parameter estimate	S.E.	Wald (χ^2)	Sig.	Odds ratio
Path interval model (200m), $R^2_N = 0.42$						
Path interval (1)	0 – 200 m	-3.013	1.102	7.466	0.006	0.049
Path interval (2)	200 – 400 m	-2.029	0.610	11.084	0.001	0.131
Path interval (3)	400 – 600 m	-1.357	0.413	10.818	0.001	0.257
Soil fertility (av.)		-2.035	0.483	17.735	0.000	0.131
Soil fertility (high)		-2.903	0.572	25.724	0.000	0.055
Constant		2.213	0.448	24.379	0.000	9.141
Euclidian interval model (200m), $R^2_N = 0.45$						
Euclidian interval (1)	0 – 200 m	-4.158	1.120	13.781	0.000	0.016
Euclidian interval (2)	200 – 400 m	-2.109	0.490	18.504	0.000	0.121
Euclidian interval (3)	400 – 600 m	-1.569	0.531	8.717	0.003	0.208
Euclidian interval (5)	800 – 1000 m	-1.639	0.639	6.578	0.010	0.194
Soil fertility (av.)		-1.988	0.479	17.240	0.000	0.137
Soil fertility (high)		-2.642	0.575	21.116	0.000	0.071
Constant		2.991	0.559	28.616	0.000	19.907
Built-up buffer model (100 m), $R^2_N = 0.21$						
Buffer (1)	0 – 100 m	-2.148	0.491	19.127	0.000	0.117
Buffer (2)	100 – 200 m	-1.109	0.390	8.088	0.004	0.330
Buffer (3)	200 – 300 m	-1.167	0.426	7.509	0.006	0.311
Soil fertility (high)		-0.984	0.417	5.577	0.018	0.374
Constant		0.809	0.261	9.568	0.002	2.245

R^2_N: Nagelkerke's R^2

Comparison of the different model performances can also be drawn from corresponding ROC curves (Fig. 3a). Overall performance, expressed as AUC, was better for the Euclidian interval and path interval models with 0.84 and 0.83, whereas the built-up buffer model only reached 0.72. The results indicate good to very good performance and are comparable with other studies (Pontius Jr and Schneider, 2001). Therefore, the Euclidian interval and path interval models explained the occurrence of SSF crop rotations better than the built-up buffer model.

Though one would expect built-up buffer zones to better represent clusters of soil fertility and water availability, the path interval and Euclidian interval models were better in capturing farmer's decision regarding SSF. The slightly better performance of the Euclidian interval model than the path interval model was associated with the regrouping of fields into fewer Euclidian interval numbers.

Table 5. Classification of SSF crop rotation.

Cutoff Value	Overall Percentage (%)	Specificity (%)	Sensitivity (%)	False neg. prediction	False pos. prediction
Path interval model (200 m)					
0.1	52.7	0	100	0	95
0.3	73.1	62.3	87.4	11	43
0.5	77.1	77.2	77	20	26
0.7	71.1	93.9	41.4	51	7
0.9	70.1	94.7	37.9	54	6
Euclidian interval model (200 m)					
0.1	53.7	18.4	100	0	93
0.3	76.6	72.8	81.6	16	31
0.5	78.6	86.8	67.8	28	15
0.7	78.1	89.5	63.2	32	12
0.9	65.2	98.2	21.8	68	2
Built-up buffer model (100 m)					
0.1	47.8	8.8	98.9	1	104
0.3	59.7	42.1	82.8	15	66
0.5	71.6	86	52.9	41	16
0.7	56.7	100	0	87	0
0.9	56.7	100	0	87	0

Regression coefficients were highest for the Euclidian interval model and lowest for the built-up buffer model (Table 4). Also regression coefficients increased with decreasing distance to the field. In general, the closer the field to the homestead, the less likely SSF occurred. While the Euclidian interval and path interval models included the perceived average and high soil fertility variables, the built-up buffer model only included high soil fertility. Again, soil fertility regression coefficients of the Euclidian interval and path interval models were higher than those of the built-up buffer model. The regression coefficients for perceived high soil fertility were higher than for perceived average soil fertility, both for the Euclidian interval and path interval models. The odds of finding SSF were with 0.016 lowest in the Euclidian interval (1) variable, i.e. the SSF was about 63 times less likely to be found in the Euclidian (1) interval than in the reference class Euclidian interval (7). Conversely, the odds were highest (0.374) for the perceived high soil fertility variable in the built-up buffer model. Hence, SSF is only about 2.7 times less likely to occur on fields with perceived high soil fertility than on those with perceived low soil fertility.

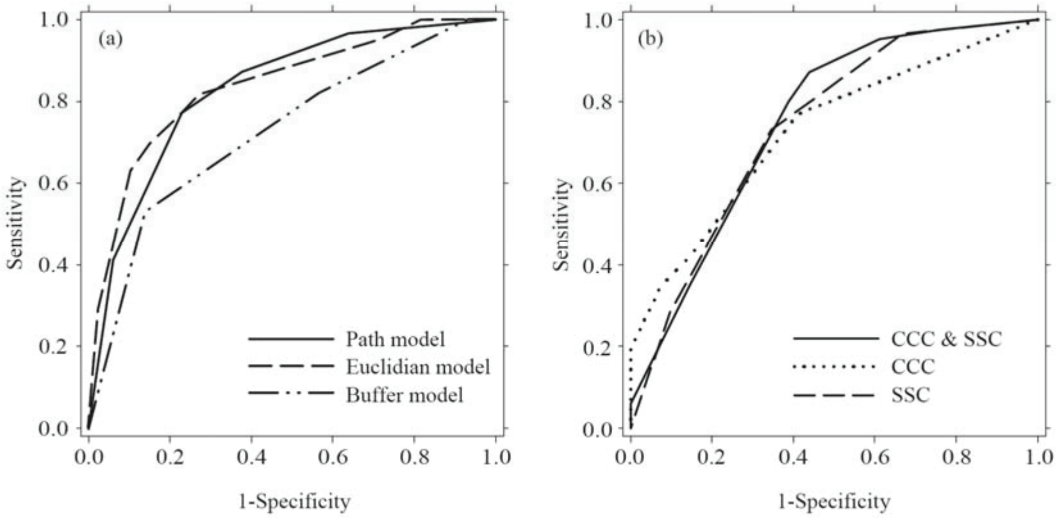


Fig. 3. ROC curves for the path model (AUC = 0.834), the Euclidian model (AUC = 0.836) and buffer model (AUC = 0.718) of SSF crop rotation (a) and ROC curves for the crop rotations CCC & SSC (AUC = 0.754), CCC (AUC = 0.735) and SSC (AUC = 0.74) based on the Euclidian model (b).

Presence or absence of SSF crop rotation was assumed to be influenced by a variety of different processes. Though water availability in the third season and number of livestock were not significant ($P < 0.05$) in the model, a weak correlation was observed between these variables and the SSF rotation. Furthermore, distance intervals (1) to (3) and (5), as well as perceived average and high soil fertility remained as explanatory variables. The model was particularly good in explaining presence or absence in the first (1) to (5) distance intervals. These findings reflected well observations made during the field survey, where remote fields were left fallow during the third season and cash cropping was practised on fertile soils close to the farm homesteads. The latter also explains well why distance as a continuous variable was dropped. With a continuous variable, more remote fields had no influence on the model but were still linked to it. Once separated into different distance intervals, its elucidating power became visible.

3.3 Maximum likelihood estimates for cash crop rotations

The Euclidian interval model was selected for analysis of further crop rotations as it performed better than the path interval and built-up buffer models. Three models were developed to investigate the effect of independent variables on cash crop dominated (CCC), cash crop-accentuated (SSC) and a combined crop rotation (CCC & SSC) (Table 6). Based on calculated R^2_N, the CCC & SSC model ($R^2_N = 0.28$) performed better than the SSC ($R^2_N = 0.22$) and CCC models ($R^2_N = 0.18$).

Table 6. Maximum likelihood estimate based on the Euclidian interval for CCC & SSC, CCC, and SSC crop rotations.

Variable		Parameter estimate	S.E.	Wald (χ^2)	Sig.	Odds ratio
CCC & SSC crop rotation model, $R^2_N = 0.28$						
Euclidian interval (1)	0 – 200 m	1.364	0.560	5.918	0.015	3.910
Euclidian interval (2)	200 – 400 m	1.049	0.409	6.594	0.010	2.855
Euclidian interval (3)	400 – 600 m	0.943	0.468	4.065	0.044	2.568
Soil fertility (av.)		2.078	0.570	13.291	0.000	7.985
Soil fertility (high)		2.703	0.621	18.971	0.000	14.928
Constant		-2.921	0.573	26.032	0.000	0.054
CCC crop rotation model, $R^2_N = 0.18$						
Euclidian interval (1)	0 – 200 m	2.5156	0.613	16.8342	0.000	12.375
Euclidian interval (2)	200 – 400 m	1.1777	0.537	4.8041	0.028	3.247
Soil fertility (high)		0.8611	0.488	3.1102	0.078	2.366
Constant		-3.0861	0.457	45.5713	0.000	0.046
SSC crop rotation model, $R^2_N = 0.22$						
Euclidian interval (2)	200 – 400 m	0.762	0.386	3.895	0.048	2.143
Euclidian interval (3)	400 – 600 m	1.169	0.450	6.750	0.009	3.220
Soil fertility (av.)		2.475	0.758	10.649	0.001	11.878
Soil fertility (high)		2.713	0.794	11.674	0.001	15.068
Constant		-3.626	0.757	22.917	0.000	0.027

R^2_N: Nagelkerke's R^2

The classification table with selected cutoff values from 0 to 1 provides an overview of the performance of the crop rotation models (Table 7). The overall percentage of correctly classified fields ranged from 55 to 69% in the CCC & SSC model, from 61 to 89% in the CCC model and from 52 to 72% in the SSC model. The CCC model thus reached highest overall percentage followed by SSC, CCC & SSC. At a cutoff value of 0.5, false negative prediction was lowest in the CCC & SSC model and highest in the SSC model. False positive prediction was, however, lowest in the case of CCC and highest in the case of CCC & SSC. For CCC crop rotation this means that none of the 201 fields were predicted false positive, whereas 21 were predicted false negative. Thus, 21 fields were erroneously classified as fields without CCC crop rotations.

The corresponding ROC curves further illustrate performance characteristics of the three models (Fig. 3b). Though overall correct prediction percentage varied considerably for 0.5 cutoff values (Table 7), all ROC curves followed a similar pattern with minimal differences between the AUC of the models. The AUC of crop rotations CCC & SSC, CCC and SSC ranged between 0.735 and 0.754. However, compared to the SSF rotation, performance was lower for cash crop influenced rotation CCC & SSC and respective sub-models. This finding was explained by competing effects, as about 18% of the surveyed fields were occupied with crop rotations other than CCC, SSC or SSF.

Table 7. Classification of CCC & SSC, CCC and, SSC crop rotations.

Cutoff Value	Overall Percentage (%)	Specificity (%)	Sensitivity (%)	False neg. prediction	False pos. prediction
CCC & SSC crop rotation model					
0.1	55.2	24.1	97.6	2	88
0.3	62.7	38.8	95.3	4	71
0.5	69.2	61.2	80	17	45
0.7	60.2	100	5.9	80	0
0.9	57.7	100	0	85	0
CCC crop rotation model					
0.1	61.2	58.9	76.9	6	72
0.3	85.1	92.6	34.6	17	13
0.5	89.6	100	19.2	21	0
0.7	87.1	100	0	26	0
0.9	87.1	100	0	26	0
SSC crop rotation model					
0.1	51.7	33.1	96.6	2	95
0.3	67.7	65.5	72.9	16	49
0.5	72.1	90.1	28.8	42	14
0.7	70.6	100	0	59	0
0.9	70.6	100	0	59	0

Distance regression coefficients decreased with increasing distance to the field. Soil fertility regression coefficients increased with perceived higher soil fertility. While the CCC & SSC included Euclidian intervals (1) to (3) as well as perceived average and high soil fertility, CCC only included Euclidian intervals (1) and (2) as well as perceived high soil fertility. This finding was also observed during the field survey, where CCC-cropped fields were encountered close to the homestead. Conversely, the SSC crop rotation included Euclidian intervals (2) and (3), as well as perceived average and high soil fertility; SSC was rather encountered on more remote fields. A noticeable feature of SSC is the fact that the regression coefficient of Euclidian interval (2) was slightly reduced, whereas the estimate of interval (3) increased again. This reduction was associated with competing effects between SSC and CCC rotations. Thus, in CCC & SSC crop rotations, a steady reduction in the regression coefficient of the Euclidian interval (1) to (3) was observed. Furthermore, non-significant perceived high soil fertility and the drop out of average soil fertility in the CCC model were related to the small number of fields assigned to the CCC crop rotation. CCC with perceived high soil fertility was found on only 20% of the fields, compared to about 42% in the SSC rotation model.

The odds of finding CCC & SSC were 14.9 times higher on fields with perceived high soil fertility than on low fertility fields. However, the odds of finding CCC & SSC in the Euclidian interval (3) model were only 2.6 times higher than in the Euclidian interval (7) model. In the CCC crop rotation model, the likelihood of finding the cash crop dominated rotation was highest in the Euclidian interval (1) and lowest in perceived average soil fertility. Regarding the SSC crop rotation model, the likelihood of finding SSC was again highest in perceived high soil fertility but lowest in the Euclidian interval model (2).

3.3 Further aspects of staple and cash crop rotations

Models for staple and cash crop rotations were developed at communal level. It was assumed that production conditions were similar in all villages, yet could slightly vary from one village to another. For instance, land availability and soil fertility can influence the development of prevailing production systems. Where per capita land availability is high and soil fertility low, staple crop-based rotations may be more pronounced than other rotations. Conversely, high soil fertility and low per capita land availability may lead to more cash crop-dominated rotations. In this study, differences in land availability and soil fertility were observed in all three villages. For instance, in the village of Thuy Ha, land availability was higher but soil fertility lower, thus leading to more staple crop-based rotations. In the village of Thuong Phuc, however, land availability was lower but soil fertility was higher, thus resulting in more cash crop-dominated rotations. Therefore, models developed at village level would differ from each other and the commune.

Though the villages exhibited some differences, the general trend was the same in every village. Additional data collected during the interview further underpinned spatial explicitness of staple and cash crop-dominated rotations. When farmers were asked to allocate staple and cash crops to different fields of an exemplary farm, cash crops were allocated to the fields close to the homestead while staple crops were distributed to more remote fields. This led to staple crop-based rotations on remote fields and cash crop-dominated rotations on close fields. Farmers argued that cash crops require more intensive care in terms of weeding, watering or pest management; hence, travel distance should be as short as possible.

4 Conclusions

This study investigated factors influencing the likelihood of a specific crop rotation to occur in ‘space’. Of 44 variables tested, 10 significantly influenced the presence/absence of a certain crop rotation pattern (SSF, CCC or SSC). Distance to the field was a major explanatory variable. Besides, occurrence of crop rotation was rather influenced by perceived soil fertility. Models including Euclidian and path intervals performed better than the model based on built-up buffer. Furthermore, results revealed that intensity of crop rotations (i.e. more cash crops per year) decreased with distance to the field and low soil fertility. The likelihood of finding cash crop-dominated rotations (CCC) was highest on nearby fields with perceived high soil fertility. This likelihood decreased with additional distance and lower soil fertility. However, the likelihood for combined staple/cash crop rotations (SSC) increased. Finally, SSC rotations were replaced by staple crop-based rotations (SSF) on remote fields. CCC and SSC rotations were mainly separated by distance while SSF and CCC or SSC were also separated by perceived soil fertility.

Albeit, the models path and Euclidian interval performed generally better, built-up buffer would be more convenient for modelling as it can be easily linked to different types of raster data (e.g. airborne or space borne sensor data and geographical maps). Furthermore, where the likelihood of crop rotations on fields with unknown farmer affiliation has to be predicted, the model path and Euclidian interval are less suitable.

Spatially explicit crop rotation models are potentially suitable to explain and predict changes in agricultural land use over space and time. They can help to acquire a better understanding of crop rotation patterns in other regions and associated nutrient flows. Thus, crop rotation models can substantially contribute to the development of site-specific crop and nutrient management strategies, especially in highly diverse landscapes such as peri-urban areas. They are also useful tools for designing different agricultural planning scenarios.

Chapter 3

Linking nutrient flows to spatially explicit crop rotations[*]

[*] This chapter is based on:
Forster D., Amini M., Menzi, H., Vu Dinh, T., Lennartz, B., 2009. Linking nutrient flows to spatially explicit crop rotations. Agriculture, Ecosystem and Environment, submitted.

Abstract

While continuous use of excess amounts of fertiliser leads to soil and water pollution, mid or long-term fertiliser deficits result in soil fertility degradation. Preferential allocation of fertilisers can cause soil fertility gradients for which site-specific nutrient management (SSNM) is suggested. Knowledge of nutrient-related management patterns of crop rotations could help combat soil fertility degradation. This study aimed at assessing nutrient flows and factors to elucidate flow variations associated with spatially explicit crop rotations in the Bac Hong commune, Hanoi province, Vietnam. Nitrogen fertiliser inputs were used as indicators for nutrient flows to staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. Average organic, inorganic and total nitrogen fertiliser inputs for SSF vs SSC & CCC, and average total nitrogen input for SSC vs CCC differed significantly. Rank transformed ANCOVA with covariates built-up buffer distance, road buffer, soil fertility, water availability during the 1st and 3rd season, relative elevation topography, plot size, and farm livestock number were examined for their explanatory power. Built-up buffer distance and plot size explained much of the variation. However, the overall explanatory power was low to moderate, reaching the highest value of 51% in the case of SSC & CCC. Remaining variations in rotation were partially explained by the different crop fertilising patterns. Comparison of mean total nitrogen inputs for paddy rice, maize and *Brassica oleraceae* plots revealed significant differences between the various crops. Furthermore, grouping of crops into crop rotations reduced variability in total nitrogen input by almost 10%. Farmers not only considered different sources of nitrogen, but also accounted for variations in seasonal fertiliser application. Crop rotations added an important temporal component to the management of nutrient flows. Temporally and spatially explicit crop rotations could bridge important gaps in understanding farm nutrient management and contribute to improving modelling of nutrient balances at different spatial scales.

Keywords: crop rotation, cropping pattern, nutrient balance, nutrient flow, nutrient management, Hanoi, Vietnam.

1 Introduction

Continuous use of excess fertiliser leads to soil and water pollution. Conversely, significant mid or long-term fertiliser deficits result in soil fertility degradation. The serious soil fertility degradation observed, especially in tropical and subtropical countries, can inevitably affect food security. Biophysical and socio-economic factors hence play a key role in soil resource management (Tittonell et al., 2005a). According to Smaling et al. (1996), the net flow of resources on the different farm fields vary in terms of organic and inorganic nutrient sources. Soil fertility is usually reported to be higher on close than on remote fields (Prudencio, 1993; Ruthenberg, 1980; Sédogo, 1993). Preferential allocation of organic resources on fields close to the homestead was either attributed to limited labour or to farmers' food security (Giller et al., 2006; Tittonell et al., 2005b). Soil fertility parameters, such as organic matter and available phosphorus, were generally highest on close fields but declined with distance (Prudencio, 1993; Sédogo, 1993). Long-term variations of land use, number of livestock and available labour may lead to the development of soil fertility gradients (Scoones and Toulmin, 1998; Smaling et al., 1997). Along these gradients, nutrient use efficiency varies considerably from one field to another (Giller et al., 2006; Vanlauwe et al., 2000a; Vanlauwe et al., 2000b).

Soil fertility gradients seem to have the 'spatially explicit' common attribute. Generally, fields close to the homestead tend to receive more fertiliser than fields further away. Vanlauwe et al. (2006) highlighted the need for site-specific nutrient management (SSNM) where soil fertility levels are considerably different. SSNM is the dynamic, field-specific management of nutrients during a specific cropping season to optimise nutrient supply and demand as a function of cycling differences in soil-plant systems (Buresh, 2007; Dobermann and White, 1999; Pampolino et al., 2007). In SSNM, which forms part of site-specific crop management (SSCM) and which is also known as precision farming, farmers adapt agronomic practices, resources and crop management as these vary across a site (Dobermann and White, 1999; Mzuku et al., 2005). Numerous studies deal with site-specific crop and nutrient management both in industrialised countries (Bachmaier and Gandorfer, 2009; Dobermann and Cassman, 2002; Kahabka et al., 2004; McCormick et al., 2009; Plant, 2001) and in developing and transition countries (Dobermann et al., 2002; Hu et al., 2007; Khurana et al., 2008; Pampolino et al., 2007; Rüth and Lennartz, 2008). The principle of SSCM and SSNM is applicable to both large and small-scale agriculture. However, while North American or some European farmers apply SSCM to fields of up to 100 ha, fields in the small-scale Asian systems, such as the peri-urban farms, may average around 300 m^2. Hence, addressing one field of 100 ha would be equivalent to addressing about 3300 peri-urban fields in Asia. Yet, management decisions on large and small fields are also based on field parcels. In other words, the farmer selects the crop and decides on the inputs (e.g. organic and inorganic fertiliser) and management practice as a function of the physical environment at field level.

The field's physical environment (Joannon et al., 2008) as well as social rules and regulations (Balent and Stafford-Smith, 1993) are important factors in land use practice. As a result, strong similarities in land use pattern among individual farms and landscape units can be observed. The physical environment (e.g. soil, water, topography, field location) influences the combination and sequence of crops in rotation. Environment and land management also influence the supply of inputs and affect the physical, chemical and biological parameters and, consequently, soil fertility. Furthermore, crop combination, frequency, sequence, and activities during crop-free periods cause rather fixed patterns in production requirements: labour, water, machinery, storage facility, and cash flow (Dogliotti et al., 2003; Joannon et al., 2008; Rounsevell et al., 2003; Struik and Bonciarelli, 1997). Hence, crop rotations allow to greatly modify the soil environment (Ball et al., 2005) and determine soil fertility improvement or exploitation over mid or long-term period.

Forster et al. (2009a) investigated crop rotations as a function of their spatial explicitness and suitability to predict land use over time for a diversified agricultural production system in the peri-urban area of Hanoi, Vietnam. Paddy rice dominated the first and second cropping season, followed by crop rotations with vegetables, maize and sweet potato (Fig. 1). Since every additional crop in rotation increases the number of possible recombinations, agricultural land cover/land use was recoded into fallow land, staple and cash crops. Vegetable, maize and sweet potato were labelled as cash crops (C), rice as staple crop (S) and fallow land was termed as F. Statistical models were developed by using a logistic regression procedure to investigate the effect of distance, field size, soil fertility, water availability, topography, and livestock on crop rotations.

Results indicated that distance to the field was a major explanatory variable. Perceived soil fertility also had a great influence on crop rotation occurrence. Furthermore, intensity of crop rotations (i.e. more cash crops per year) decreased with distance to the field and low soil fertility. The likelihood of finding cash crop-dominated rotations (CCC) was greatest on close fields with perceived high soil fertility. With additional distance and lower soil fertility, the likelihood also decreased, but increased with cash crop-accentuated (SSC) rotations. CCC and SSC rotations were mainly separated by distance, however, SSF, CCC or SSC were also separated by perceived soil fertility. The study revealed that spatially explicit crop rotation models have the potential to explain and predict agricultural land cover/land use change over space and time and contribute to improving site-specific crop and nutrient management.

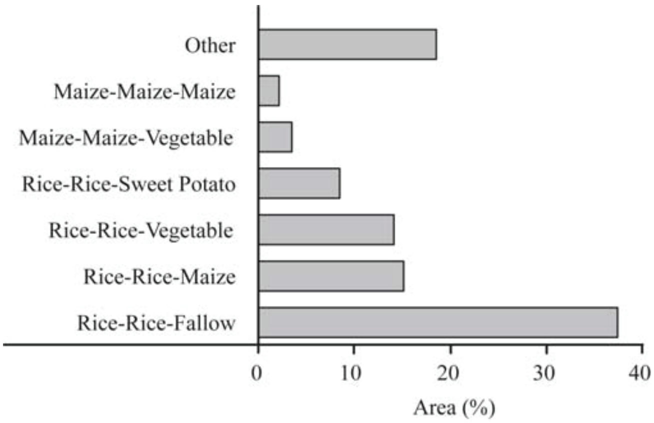


Fig. 1. Proportion of distinct crop rotations in the Bac Hong commune, Hanoi province, Vietnam.

Therefore, the choice of a crop rotation is a process closely linked with SSCM and SSNM. Where soil fertility gradients and spatial factors are similar, certain crop rotations may appear more frequent than others. Furthermore, production requirement patterns (e.g. use of organic and inorganic fertilisers) for different crop rotations may also be similar. This study aimed at assessing nutrient flows and factors explaining variations in flows associated with spatially explicit crop rotations. Nitrogen (N) was used as indicator for plant nutrition and based on the following hypotheses: (i) organic, inorganic and total fertiliser nitrogen inputs differ significantly between each crop rotation, (ii) built-up buffer distance, road buffer, soil fertility, water availability during 1st and 3rd season, relative elevation topography, plot size, and farm livestock number are key factors for gradients in fertiliser inputs and (iii) variation in fertiliser inputs to crops also partially explains variations in crop rotation input.

2 Materials and Methods

2.1 Study environment

The Bac Hong commune, situated in the district of Dong Anh (21° 8´ 14´´ N; 111° 49´ 44´´ E) about 5 km north of the capital Hanoi, Vietnam, was studied because of its diverse production systems. Agriculture is the main source of income and the land is distributed around a centrally organised and densely built-up area. The commune covers 7.2 km^2 of flat land (elevation range 8 – 12 m above sea level), of which 5.1 km^2 are allocated to agricultural production. Mixed farming, including crop and livestock production, is a widespread practice among farmers. The regional soils belong to the Acrisols, Plinthic Acrisols or Hapli Plinthic Acrisols soil groups (FAO-UNESCO classification), respectively (Nguyen et al., 2004). They are generally of light texture, varying between loamy sand and light loam, with a low organic matter content (>1.26%) and a slightly acid to neutral pH (H_2O) of 6.7 – 7.1. The irrigation and drainage system covers the entire cropping area in all three villages. During the first and second growing seasons (mid-February to mid-June and mid-June to mid-October) drainage of excess water is important. However, irrigation is necessary during the third growing season (October to February). Paddy rice (*Oryza s.* L.) is the major crop in the first and second growing seasons (Table 1). However, on elevated terrain, farmers alternatively grow maize (*Zea maize* L.) or sweet potato (*Ipomoea batatas* L.). While most of the land remains fallow in the third growing season, farmers plant cash crops on a reduced land area. Aside from annual crops, a considerable area is reserved for perennial crops.

2.2 Selection of farms and fields

The Bac Hong commune is formed by six different villages, three of which were selected for this study (Thuy Ha, Thuong Phuc and Ben Chung). In each village, the village leading committee was asked to provide a list of 25 farmers well representing the village. From the lists provided and to spatially cover the entire region (Fig. 2), 12, 12 and 10 farmers were selected from Thuy Ha, Thuong Phuc and Ben Chung, respectively. On average, each of the 34 selected farmers had about 5 – 7 fields, thus amounting about 201 fields for all three villages. The average size of each farm was about 0.2 ha. The size of the fields ranged from small (79 m^2) to large (862 m^2) and averaged about 305 m^2.

Table 1. Crops grown in major (X) and minor (x) seasons in the Bac Hong commune, Hanoi province.

	Season[1)]		
	1st	2nd	3rd
Annual crops			
Rice paddy (*Oryza s.* L)	X	X	-
Maize (*Zea maize* L)	x	x	X
Sweet potato (*Ipomoea batatas* L)	x	x	X
Peanut (*Arachis hypogaea* L)	x	x	X
Soybean (*Glycine max* L)	x	x	X
Cabbage (*Brassica oleraceae var. capitata*)	x	x	X
Kohlrabi (*B. o. var. gongylodes*)	x	x	X
Broccoli (*B. o. var. botrytis*)	x	x	X
Pak-choi (*B. rapa spp. chinensis*)	x	x	X
Tomato (*Lycopersicon esc. var. esculentum*)	x	x	X
Eggplant (*Solanum melongena*	x	x	X
Cucumber (*Cucumis sativus* L.)	x	x	X
Pumpkin (*Cucurbita maxima*)	x	x	X
Perennial crops	X	X	X
Peach (*Prunus* sp.)	X	X	X
Star fruit (*Averrhoa carambola* L.)	X	X	X
Longan (*Dimocarpus longan*)	X	X	X
Lychee (*Litchi chinensis*)	X	X	X
Mango (*Mangifera domestica* L.)	X	X	X
Sapodilla (*Manilkara zapota* L.)	X	X	X
Banana (*Musa* sp.)	X	X	X

[1)] 1st season: mid-February to mid-June, 2nd season: mid-June to mid-October, 3rd season: mid-October to mid-February

2.3 Field/plot typology and data collection in general

The favourable climate and proximity to urban Hanoi allowed an intensive, continuous cropping system, but required a well elaborated field/plot typology and respective data management methods. Like in the other rice growing areas, the fields were usually demarcated by bunds, separating the own field from neighbouring fields to prevent water drainage. Since these field boundaries were permanent, they did not change from season to season or from year to year. However, especially during the third growing season, farmers frequently subdivided their fields into smaller plots. Therefore, each field consisted of one to many plots adjustable in size. As plots structures were of temporary nature, they had a specific start and end, which usually coincided with the start and end of the crop.

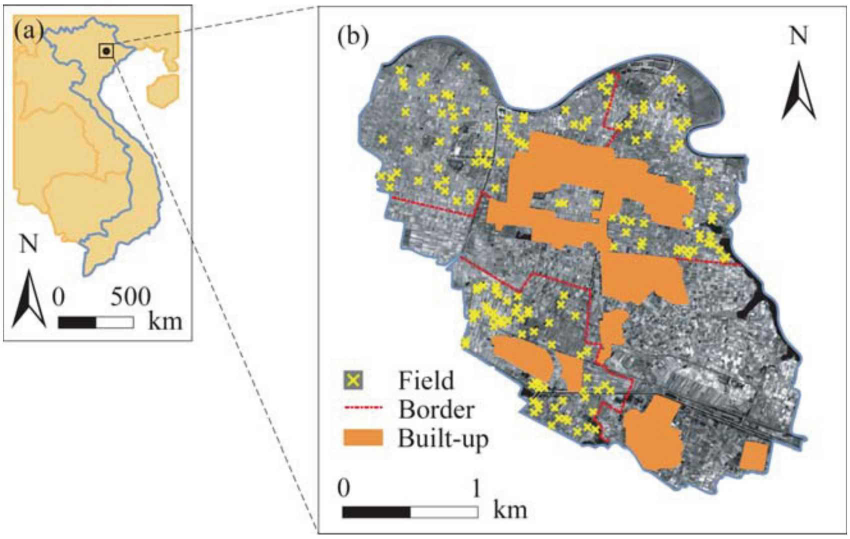


Fig. 2. The study area of Vietnam (a) and Bac Hong commune with built-up area and farmers' fields (b).

Semi-structured interview techniques, a tailored database system (MSAccess®) and differential GPS system (Leica GS20®) were used to better cope with agricultural diversity during data collection. During a transect walk, soil conditions (e.g. soil quality) and management practice of each field were discussed and recorded in a farm map. Homestead and fields were recorded by GPS. Instead of determining a simple field centre point, the plot shape was recorded to assess field/plot size. Post-processing of GPS field data (i.e. differential correction) with Leica GIS DataPro® increased positioning to sub-meter accuracy. Interviews were conducted on all 34 farms. The survey took place in two consecutive years (2005/2006) and was carried out at the time of the third growing season (Oct. 2005–Jan. 2006 and Oct. 2006–Jan. 2007).

2.4 Nutrient flows and fertiliser management

The study focused on nutrient flows linked to crop rotations. Despite the existence of tools such as NUTMON (Smaling and Fresco, 1993; Van den Bosch et al., 1998a) or NUFLUX (Menzi et al., 2002) for nutrient budgeting, input and output variables are generally based on estimates or recommendations, either obtained in a participatory process together with the farmer or use of empirical transfer functions. Uncertainties associated with these estimates can be considerable (Oenema et al., 2003; Smaling et al., 1997). To partially reduce these uncertainties, the study focused on nutrient inputs only. Since nitrogen is of main concern to farmers, it was chosen as an indicator element for the entire nutrient management study. To estimate inputs to a specific crop, applications of inorganic (*N_inorg*) and organic (*N_org*) fertiliser nitrogen were cumulated and resulted in total nitrogen input (IN_{tot}) per field and crop rotation (Eq. 1).

$$IN_{tot} = \sum_{i=1}^{P} \sum_{j=1}^{N} (N\_org_{ij} + N\_inorg_{ij}) \qquad (1)$$

where *P* and *N* represent the number of plots and crops per field.

Due to their peri-urban location and vicinity to the market, various inorganic fertilisers, such as urea, superphosphate, potassium chloride, and a further 16 multi-nutrient fertilisers were accessible to the farmers. Organic manure used for agricultural production was locally collected from cattle, pig and poultry. Pig and cattle manure was the major source of organic input. Solid manure was usually mixed with rice straw or lime before it was stacked on a manure heap or in pits covered by a tarpaulin and soil on the field (Nguyen Duy et al., 2006; Vu Dinh et al., 2006). In addition to manure produced on the farms, about four different types of industrially enriched compost fertilisers (i.e. organo-mineral fertilisers) were used especially for vegetable production.

While visiting the fields, each farmer was interviewed on the amount of organic and mineral fertilisers applied. The farmers were shown an illustrated list of commercial organic and mineral fertilisers as well as farm manures. Cans of different sizes were used to approximate the amount of chemical fertiliser applied. As plant available nitrogen in organic fertiliser is difficult to assess, total nitrogen content was used to calculate nutrient flows. Consequently, the nitrogen contribution from organic fertiliser is slightly overestimated.

2.6 Data analysis

As in Forster et al. (2009a), the data was grouped into staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. Additional data was computed for a combined rotation (SSC & CCC). Crop rotations were compared for their inorganic, organic and total nitrogen inputs. As the Sapiro-Wilk test (Shapiro and Wilk, 1965) resulted in non-normal distributed data, and the Levene's test (Levene, 1960) indicated heterogeneity of variance in different groups (Table 2), the non-parametric Kruskal-Wallis test (Kruskal and Wallis, 1952) was applied to compare nitrogen inputs between crop rotations.

In a first step, a planned comparison (Field, 2005) of analysis of variances was carried out to reduce family-wise error rate (Type 1 error rate). Nitrogen inputs of rotations with two crops per year (SSF) were first compared to rotations with three crops per year (SSC & CCC). A second comparison examined the differences between SSC and CCC. In addition to the descriptive parameters, the coefficient of variation, i.e. an index of the overall variation or heterogeneity of a given variable, was used as a comparison.

Table 2. Statistical methods applied in the study.

Statistical method	Procedure
Sapiro-Wilk test	Analysis of normal data distribution
Levene's test	Analysis of heterogeneity of variance
Kruskal-Wallis test	Non-parametric analysis of variance
Rank transformed ANCOVA	Non-parametric analysis of covariance
Mann-Whiney test	Non-parametric post-hoc procedure

In a second step, the study analysed the effects of different explanatory variables, such as distance, field size, soil fertility, water availability, topography, and livestock on total nitrogen (i.e. organic and inorganic) fertiliser use in crop rotations. Average fertiliser recommendations were used to judge fertiliser surplus or deficits among crop rotations and explanatory variables (Table 3).

Distance was measured as built-up buffer distance, i.e. distance from the border of the built-up area to the farmer's field. The buffer applied represents the distance (i.e. distance intervals) to the fields assigned by the GIS multiple buffer functions.

Field size was recorded by a differential GPS system as described in section 2.3. Soil fertility was evaluated as perceived by the farmer, and each field was discussed and compared with other fields during the transect walk. The farmer could choose from three categories: 0 = infertile, 1 = medium, 2 = fertile soil.

Water availability was addressed for each growing season and included water through rainfall as well as water supplied by the irrigation system. Farmers were asked to assess water availability according to two categories: zero indicated no available water and 1 that sufficient water was available.

Table 3. Summary of explanatory variables used in analysis of nutrient patterns.

Variable Name		Type	Unit
Dependent variables			
Total fertiliser nitrogen		Continuous	kg ha^{-1}
Organic fertiliser nitrogen		Continuous	kg ha^{-1}
Inorganic fertiliser nitrogen		Continuous	kg ha^{-1}
Independent variables			
Buffer, built-up area – field	100 m	Categorical	0 – 8
Road buffer, road – field	25 m	Categorical	0 – 3
Soil fertility		Categorical	0 – 2
Water availability during 1st season		Categorical	0 – 1
Water availability during 3rd season		Categorical	0 – 1
Relative elevation topography		Categorical	0 – 2
Plot size		Continuous	m^2
Farm livestock number		Continuous	LU[1)]

[1)] Livestock unit calculated according to FAO

Relative elevation topography is a locally used term to evaluate the elevation of a field compared to its neighbouring fields. In a cascading system, the relative elevation topography indicates whether a field mainly receives water from neighbouring fields (sunken field) or whether it is at the top of the cascade and receives water directly from the irrigation channels. Together with the interviewer, the farmer could choose from three categories (0 = sunken, 1 = medium, 2 = high).

Data on livestock numbers was collected during the survey 2005/2006. The average number of cattle, pigs and poultry was recorded and transferred into universal livestock units according to FAO (2003).

To further explore the covariates influencing the dependent variable nitrogen, SSF, SSC & CCC were subjected to rank transformed ANCOVA. Effect size, a measure of strength of the relationship between two variables, was calculated according to Rosnow and Rosenthal (2005).

In the last step, three major crops (paddy rice, maize, *Brassica oleraceae*) were analysed for differences in nitrogen inputs. Tests were conducted according to Table 2. The critical value of significance in the Mann-Whiney test (Mann and Whitney, 1947) was corrected using a Bonferroni correction (Bonferroni, 1936). SPSS® software package was used for statistical analysis.

3 Results and Discussion

3.1 Differences in nitrogen inputs between crop rotations

In general, fertiliser nitrogen inputs varied considerably between the different crop rotations and levels of comparison (Table 4). In the first comparison, the SSC & CCC rotation reached the highest maximum value for inorganic fertiliser input with 643 kg ha^{-1}, while SSF amounted to 383 kg ha^{-1}. Use of organic fertiliser nitrogen varied strongly, ranging from zero for both SSC & CCC and SSF rotations to 239 kg ha^{-1} for the SSC & CCC rotation. As a result, total nitrogen (i.e. sum of inorganic and organic fertiliser nitrogen) was considerably higher for SSC & CCC (maximum 753 kg ha^{-1}) than for SSF (452 kg ha^{-1}). Minimum use of total nitrogen was recorded for SSF (minimum 99 kg ha^{-1}) compared to 169 kg ha^{-1} for SSC & CCC. On average, the SSC & CCC rotation received significantly higher amounts ($P < 0.05$) of inorganic, organic and total fertiliser nitrogen (384, 112 and 496 kg ha^{-1}, respectively) than the SSF rotation. In the second comparison, analysis of SSC & CCC crop rotation revealed similar trends among fertiliser sources, but less distinct than in the first comparison. The highest inorganic fertiliser nitrogen value for CCC was recorded at maximum 643 kg ha^{-1} compared to 581 kg ha^{-1} for SSC. Lowest and highest values of organic fertiliser nitrogen use was in both cases recorded for CCC with zero and 239 kg ha^{-1}, respectively. Total nitrogen use was higher for CCC (753 kg ha^{-1}) than for SSC (686 kg ha^{-1}). Lowest total nitrogen was recorded for SSC (169 kg ha^{-1}) compared to CCC (234 kg ha^{-1}). The total average nitrogen value for SSC (475 kg ha^{-1}) differed significantly ($P < 0.05$) from that of CCC (543 kg ha^{-1}). Conversely, average inorganic and organic nitrogen use did not vary significantly.

Though large variations were observed for total nitrogen inputs, it is interesting to note that average inputs were similar to the calculated fertiliser recommendations for crop rotations (Table 5). Only the total average input for SSC was somewhat higher than the reference.

Table 4. Summary of statistics for crop rotations: staple-staple-fallow (SSF), staple-staple-cash and cash-cash-cash (SSC & CCC) in part (a), staple-staple-cash (SSC) and cash-cash-cash (CCC) in part (b), and total, organic and inorganic fertiliser nitrogen.

	N	Min (kg ha^{-1})	Max (kg ha^{-1})	Mean (kg ha^{-1})	C.V. (%)
a)					
Total fertiliser					
SSF	85	99	452	261a	27
SSC & CCC	78	169	753	496b	27
Organic fertiliser					
SSF	85	0	189	52a	85
SSC & CCC	78	0	239	112b	54
Inorganic fertiliser					
SSF	85	74	383	209a	32
SSC & CCC	78	147	643	384b	34
b)					
Total fertiliser					
SSC	53	169	686	475a	26
CCC	25	234	753	543b	27
Organic fertiliser					
SSC	53	15	220	109a	55
CCC	25	0	239	119a	52
Inorganic fertiliser					
SSC	53	147	581	366a	33
CCC	25	193	643	424a	35

Different letters indicate significant difference at $P < 0.05$.

Additionally, variability of organic fertiliser inputs is high for all rotations. Some fields received large amounts of organic nitrogen inputs (239 kg ha^{-1}), equivalent to about 52 t ha^{-1} of farmyard manure with a nitrogen content of 0.46% (Vu Dinh et al., 2006). On other fields, however, farmers did not apply any organic fertiliser at all. On average, CCC & SSC received about 24 t ha^{-1} and SSF 11 t ha^{-1}, corresponding to 8.1 and 5.6 t ha^{-1} per crop, respectively. Thus, average organic fertiliser input per crop was 2.5 t ha^{-1} higher for the CCC & SSC rotation than for SSF. In the Bac Hong commune, the likelihood for the SSF rotation to occur increased with distance from homestead to field and low soil fertility and remote fields thus receiving less organic fertiliser than close fields.

Furthermore, the coefficient of variation differed considerably between inorganic and organic fertiliser nitrogen inputs. However, the coefficient of variation in total nitrogen use was lower than for respective fractions; an indication that farmers partially accounted for contributions from different sources of nitrogen.

3.2 Effects of different explanatory variables on total nitrogen fertiliser use

Table 6 presents the effects of different explanatory variables on fertiliser surplus or deficit for SSF, SSC & CCC crop rotations. Average fertiliser recommendations for respective crop rotations (Table 5) were used as reference to classify nitrogen surplus and deficits.

Table 5. Nitrogen fertiliser recommendation for crop rotations: staple-staple-fallow (SSF), staple-staple-cash (SSC), cash-cash-cash (CCC) and selected crops rice paddy, maize and *Brassica oleraceae*.

Rotation, crops	Average N (kg ha^{-1})
SSF	250
SSC	418
CCC	503
Paddy rice [1)]	125
Maize[1)]	150
Brassica oleraceae[2)]	185

Sources: [1)] FAOSTAT, 2005, [2)] Soil and Fertiliser Institute, Vietnam, 2006, adapted for *Brassica oleraceae*.

Frequency of nitrogen surplus or deficit was expressed as percentage of the total number of fields in the respective category. Differences in rotations and variables were considerable; nevertheless, important trends could be observed. Built-up buffer indicated an increased number of fields with a fertiliser surplus in the first two buffers for SSC and CCC, while fertiliser surplus and deficit was uneven for SSF. Road buffer revealed a heterogeneity and did not seem to have an important effect on fertiliser application. Fertiliser surplus on fields with perceived high soil fertility was more frequent for SSF and SSC than for CCC. Conversely, fertiliser surplus for CCC was even more frequent on fields with perceived low soil fertility. Plot size indicated a general trend; fertiliser surplus on small plots was more frequent than on large fields.

Table 6. Field frequency with surplus or deficit in total nitrogen fertiliser application expressed in percent for crop rotations: staple-staple-fallow (SSF), staple-staple-cash (SSC), cash-cash-cash (CCC), and different explanatory variables.

	SSF[1] (%)		SSC[2] (%)		CCC[3] (%)	
	<	>	<	>	<	>
Built-up buffer (m)						
0–200	25	75	23	77	18	82
200–400	52	48	16	84	50	50
400–600	64	36	60	40	100*	0
>600	40	60	100*	0	0	0
Road buffer (m)						
0–50	44	56	37	63	37	63
50–100	36	64	13	87	17	83
100–150	60	40	0	100*	0	0
Soil fertility						
Low	46	54	50	50	0	100*
Medium	42	59	27	73	27	74
High	40	60	29	71	50	50
Plot size (m^2)						
0–200	30	70	14	86	0	100*
200–400	45	55	27	73	27	73
400–600	57	43	20	80	50	50
>600	57	43	100*	0	75	25
Water av. 1st season						
low	35	65	32	68	39	61
high	56	44	17	83	14	86
Water av. 3rd season						
low	43	57	32	68	27	73
high	44	56	17	83	40	60
Rel. terrain topography						
sunken	43	57	0	100*	0	100*
medium	43	57	26	74	29	71
high	46	54	46	54	43	57
Total livestock number[4]						
0–4	44	56	32	68	35	65
4–8	45	55	33	67	0	100*
8–12	0	100*	0	100*	25	75

Fertiliser recommendations [1] 250 kg N ha^{-1}; [2] 418 kg N ha^{-1}; [3] 503 kg N ha^{-1}
[4] Livestock Units (LU); * One value only.

Water availability observed in the 1st season for SSC and CCC indicated that fields with high water availability had a more frequent fertiliser surplus than those with low water availability. For SSF, however, a more frequent fertiliser surplus was observed in fields with low water availability. Also as regards water availability in the 3rd season, fertiliser surplus frequency had increased on fields with low water availability for SSF and CCC, but not for SSC. As regards relative elevation topography, the trend was more distinct; frequency of fertiliser surplus for all rotations was generally higher on sunken than on high fields. In the case of total livestock number, frequency of fertiliser surplus tended to be higher on farms with a greater number of livestock.

Though no clear trend was observed for SSF, built-up buffer distance could be a steering variable for nitrogen. The more remote the field, the less total nitrogen it receives. Low soil fertility could also play a key role in fertiliser practice. However, since the rather opposite trend was observed for SSF and SSC than for CCC, it was difficult to determine a clear trend. Plot size seemed to have an influence on the amount of fertiliser applied. The smaller the plot, the more fertiliser nitrogen it receives. Finally, farm livestock number may have affected organic nitrogen inputs. The higher the number of farm animals, the greater the amount of organic fertiliser nitrogen applied.

3.3 Exploring covariates for nitrogen inputs

Rank transformed ANCOVA was used to further explore the influence of independent variables on total, organic and inorganic fertiliser nitrogen. A significant difference between the nitrogen inputs and SSC & CCC and SSF crop rotations led to separate analysis of covariates. For SSF crop rotation, variability in inorganic and total fertiliser nitrogen could not be explained with the tested covariates. In other words, farmers used inorganic fertilisers for SSF rotation regardless of their perceived soil fertility. Thus, only covariates explaining variation in organic fertiliser inputs are presented (Table 7). Soil fertility was negatively correlated with organic nitrogen input, yet at a just below significant level. Contrarily, farm livestock number was positively correlated with organic nitrogen input and proved to be highly significant at $P < 0.001$. This indicates that availability of organic fertiliser was the most important parameter controlling its application. Farm livestock number underpinned the good correlation between livestock and organic nitrogen inputs with a medium to large effect size (r) of 0.46 (Cohen, 1968). Soil fertility, however, with an 0.21 r value only reached a small to medium effect size. Overall, soil fertility and farm livestock number accounted for about 24% of the variation in organic fertiliser input.

Table 7. Rank transformed ANCOVA for crop rotations: staple-staple-fallow (SSF) and organic fertiliser nitrogen (n = 85).

Parameters	B	S.E.	t	Sig.	*r*
Intercept	42.10	6.62	6.36	0.000	
Soil fertility	-6.79	3.46	-1.96	0.053	0.21
Farm livestock No.	6.33	1.35	4.68	0.000	0.46
R^2	0.24				

As average organic and inorganic nitrogen fertiliser inputs for SSC and CCC crop rotation (section 3.1) showed no significant difference, both SSC and CCC data sets were combined to rotation SSC & CCC for further analysis of covariates. Built-up buffer distance, perceived soil fertility and plot size revealed a significant negative correlation ($P < 0.001$) with total nitrogen input (Table 8). Also in the case of inorganic nitrogen input, all three covariates showed a significant negative correlation ($P < 0.001$). These variables reveal that 44% of the variation in inorganic fertiliser application could be accounted for. As for the SSF crop rotation, the covariate farm livestock number had a positive effect ($r = 0.27$, $P < 0.05$) on organic nitrogen fertiliser input for SSC & CCC. However, instead of perceived soil fertility as observed for SSF, plot size proved to have a negative correlation with input of SSC & CCC ($r = 0.25$, $P < 0.05$). Plot size and farm livestock number explained only 12% of the variation. Although covariates of fertiliser fractions were expected to explain variation in total nitrogen inputs, only built-up buffer distance, perceived soil fertility and plot area had an influence on total nitrogen inputs. Aside from perceived soil fertility, effect sizes for built-up buffer distance and plot size were higher for total nitrogen use than for fertiliser fractions. Large effect sizes were achieved with a 0.59 and 0.54 r value for plot size and built-up buffer distance, while perceived soil fertility reached a medium effect size with 0.39. Overall, the covariate built-up buffer distance, plot size and perceived soil fertility explained about 51% of data variability in total nitrogen input for SSC & CCC.

Generally, not only the mean values of nitrogen fertiliser inputs varied between SSF, SSC & CCC (section 3.1), but also the developed models were considerably different. Though a clear trend was observed between soil fertility, plot size and total nitrogen input (Table 6), inorganic and total fertiliser nitrogen inputs did not at all respond to these covariates in SSF rotation. The model's explanatory power ($R^2 = 0.24$) was rather limited and attributed to three possible reasons. Firstly, SSF was more likely to be encountered on remote fields than on close fields (Forster et al., 2009a). Secondly, distance as such may not have played a key role since the fields are located far from the homestead. Additionally, fields further out are generally larger and closer to the local unit of one Sau (350 m^2) for which paddy rice fertiliser recommendations exist. Thus, plot size did not appear as explanatory variable for SSF total nitrogen inputs. Finally, variability in organic fertiliser input may also be explained by the fact that farmers did not apply manure frequently, and that manure applications were characterised by a wide range of values and large amounts of up to 41 t ha^{-1} y^{-1} for SSF rotation.

Table 8. Rank transformed ANCOVA for crop rotations: staple-staple-cash & cash-cash-cash (SSC & CCC), and total, organic and inorganic fertiliser nitrogen (n = 78).

Parameters	B	S.E.	t	Sig.	*r*
N Total					
Intercept	102.81	9.12	11.27	0.000	
Buffer distance	-6.25	1.11	-5.61	0.000	0.54
Soil fertility	-11.18	3.36	-3.33	0.001	0.36
Plot area	-0.06	0.01	-6.33	0.000	0.59
R^2	0.51				
N organic					
Intercept	41.64	5.86	7.10	0.000	
Plot area	-0.03	0.01	-2.22	0.030	0.25
Farm livestock No.	2.07	0.86	2.41	0.018	0.27
R^2	0.12				
N inorganic					
Intercept	102.24	9.71	10.53	0.000	
Buffer distance	-5.48	1.19	-4.63	0.000	0.47
Soil fertility	-12.73	3.58	-3.56	0.001	0.38
Plot area	-0.06	0.01	-5.37	0.000	0.52
R^2	0.44				

Conversely, for SSC & CCC rotation, plot size revealed a significant negative correlation for all input types. The smaller the field, the more inputs it received. Thus, it seems that farmers had difficulty in adjusting fertiliser application rates to plot size. Furthermore, the many different types of inorganic fertilisers available on local markets (section 2.4), each with varying nitrogen contents, could have influenced and complicated correct dosing. The negative correlation between built-up buffer distance and inorganic and total fertiliser was explained by small differences between SSC and CCC. Though, mean organic and inorganic fertiliser nitrogen inputs did not differ statistically in the Kruskal-Wallis test (section 3.1), a small negative gradient in inorganic fertiliser input between the rotations was observed. A negative correlation developed, as SSC rotation tended to appear farther out than CCC (Forster et al., 2009a), and fields with SSC rotation tended to receive less inorganic or total fertiliser.

Additionally, close fields were easier to visit and look after, thus resulting in higher fertiliser inputs. Finally, since SSC & CCC rotations consisted of different crops, farmers may have adjusted fertiliser application rates, which could have further influenced nitrogen inputs.

3.4 Nitrogen inputs for different crops

The variation in total nitrogen fertiliser inputs was mainly explained by built-up buffer distance, plot size and perceived soil fertility. The remaining unexplained variation was partially associated with different crops grouped into SSC or CCC (Table 9). Fertiliser nitrogen inputs to crops varied for inorganic, organic and total nitrogen, but the range was similar for paddy rice, maize and *B. oleraceae* crops. The lowest minimum inorganic nitrogen input was observed for paddy rice (32 kg ha^{-1}), while *B. oleraceae* and maize recorded 44 and 58 kg ha^{-1}, respectively. The largest maximum amount was observed for maize (330 kg ha^{-1}) followed by *B. oleraceae* (324 kg ha^{-1}) and paddy rice (303 kg ha^{-1}). Compared to *B. oleraceae* crops (138 kg ha^{-1}) and paddy rice (113 kg ha^{-1}), maize with 181 kg ha^{-1} had the highest and significantly different mean inorganic fertiliser input ($P < 0.0167$). Organic fertiliser input ranged between 0 kg N ha^{-1}, observed for all three crops, and 149 kg N ha^{-1}, observed for paddy rice. Though not significantly different, the mean organic nitrogen input was highest for *B. olearaceae* (41 kg ha^{-1}) followed by paddy rice (34 kg ha^{-1}) and maize (32 kg ha^{-1}). Finally, the lowest minimum total nitrogen fertiliser input of 43 kg ha^{-1} was observed for paddy rice, followed by 54 kg ha^{-1} for *B. oleraceae* and 69 kg ha^{-1} for maize. The highest value for total nitrogen input of 356 kg ha^{-1} was observed for maize compared with 338 and 325 kg ha^{-1} for *B. oleraceae* and paddy rice, respectively. Again, maize achieved a statistically significant higher mean total nitrogen input (213 kg ha^{-1}; $P < 0.0167$) than other crops. However, the mean nitrogen input for *B. oleraceae* (180 kg ha^{-1}) and paddy rice (147 kg ha^{-1}) also differed significantly.

The inputs varied substantially between the different crops. As regards total nitrogen, the grouping of crops into SSC or CCC contributed to the variability of SSC & CCC rotation. Fertiliser inputs were generally higher than the recommendations listed in Table 5. Mean total fertiliser input on maize exceeded the recommended value of 60 kg ha^{-1}. Farmers explained the high application rate with the growing of sweet maize cultivars, as application of increased amounts of fertiliser sweetened the maize. Thus, maize was not only used as feed for animals, but also for human consumption. Furthermore, sweet potato and leguminous crop rotations (not mentioned in Table 5) may have also contributed to their variability, as their mean and standard deviations differed from the listed crops. Finally, similar to crop rotations (section 3.1), coefficients of variation were clearly higher for organic and inorganic fertiliser nitrogen inputs than for total nitrogen.

Table 9. Summary of statistics for paddy rice, maize and *Brassica oleraceae,* as well as total, organic and inorganic fertilizer nitrogen.

	N	Minim (kg ha^{-1})	Maxim (kg ha^{-1})	Mean (kg ha^{-1})	C.V. (%)
Total fertiliser					
Rice paddy	297	43	325	147a	37
Maize	82	69	356	213b	33
B. oleraceae	53	54	338	180c	43
Organic fertiliser					
Rice paddy	297	0	149	34a	81
Maize	82	0	136	32a	89
B. oleraceae	53	0	145	41a	97
Inorganic fertiliser					
Rice paddy	297	32	303	113a	45
Maize	82	58	330	181b	39
B. oleraceae	53	44	324	138a	53

Different letters indicate significant difference at $P < 0.0167$.

3.4 Additional aspects of fertiliser management

The results revealed that farmers used organic inputs on SSF and SSC & CCC fields. The assumption that farmer saved on fertilisers by applying less organic fertiliser on remote fields could not be confirmed by the relationship between organic N inputs and built-up buffer distance. Management of organic fertiliser certainly benefited from the almost flat land and the reasonably good road infrastructure, thus facilitating transport to the fields. However, rank transformed ANCOVA, carried out separately for SFF and SSC & CCC rotations, revealed that within each group, built-up buffer distance did not appear significant. Yet, the mean organic nitrogen input of SSF (25.8 kg ha^{-1}) was considerably lower and significantly different for SSC & CCC (37.3 kg ha^{-1}). As the SSF crop rotation is more likely to be encountered on remote fields, it became apparent that farmers did save on organic fertiliser. First, farmers applied manure on close fields with an increased number of cash crops. If enough manure remained, it was applied to fields further out dominated by staple crops. Livestock number seemed to play an important role, as availability of organic fertiliser was the key parameter controlling its use. Furthermore, the very high coefficient of variation (85%) in organic inputs of SSF rotation, compared to that of SSC & CCC (54%), confirms the assumption that SSF fields only sporadically received manure. Additional data collected during the interview provided a similar picture. When farmers were asked to allocate organic and inorganic fertiliser to different fields of an exemplary farm, most of the organic fertiliser was applied to fields close to the homestead. Conversely, inorganic fertiliser was rather spread on remote fields. Farmers argued that organic fertiliser should be used on all fields, however, due to cost factors, they would try to economise fertiliser input.

Likewise, in the case of total nitrogen inputs with crop rotations (Table 4), addition of organic and inorganic fertiliser to total nitrogen inputs of selected crops (i.e. paddy rice, maize and *Brassica oleraceae*) also reduced variation in data (Table 9). When different crops were grouped into rotations, the coefficient of variation of total nitrogen input was almost 10% less compared to single crops. Furthermore, remaining variation in data of crop rotations was better explained by built-up buffer distance, plot size and soil fertility (section 3.3). However, if the same covariates were tested on the individual crops corresponding to the rotations, the informative value was further reduced, reaching 22, 6 and 17% for total, organic and inorganic fertiliser nitrogen, respectively. Thus, by grouping crops into rotations it was possible to better account for seasonal variation regarding organic, inorganic and total nitrogen input.

Crop rotations were found to be spatially explicit and vary with production conditions (Forster et al., 2009a). For instance, where per capita land availability is high and soil fertility low, staple crop-based rotations may be more frequent. Contrarily, high soil fertility and low per capita land availability may lead to more cash crop-influenced rotations. Furthermore, cash crop-dominated rotations were more likely to be found close to the village, while staple crop-based rotations dominated on remote fields. As each rotation has its own associated nutrient flows in terms of organic and inorganic fertiliser input, they also became spatially explicit. However, crop rotations per se have a temporal nature, indicating the sequence of crops over a defined period of time (e.g. one year). Therefore, nutrient flows linked to crop rotations could add a spatial and temporal component to nutrient balances.

5 Conclusion

This study investigated nutrient flows associated with spatially explicit crop rotations. Organic, inorganic and total nitrogen fertiliser inputs were used as indicators for nutrient flows. Nitrogen inputs for SSF and SSC & CCC, and total nitrogen inputs for SSC & CCC were found to differ significantly. The covariates of built-up buffer distance, plot size and soil fertility partially explained variation in inorganic and total fertiliser input for SSC & CCC. Conversely, plot size and number of farm livestock better explained partial variation of organic fertiliser use. Only the covariates of soil fertility and farm livestock number correlated with the organic input for SSF rotation. Though the built-up buffer distance and plot size reached large effect sizes, their overall explanatory power was low to moderate, reaching the highest value of 51% for SSC & CCC. Remaining variation in rotations was greatly affected by different crop fertilising patterns. For paddy rice, maize and *B. oleraceae* crops, mean total nitrogen inputs differed significantly.

Furthermore, the grouping of crops into crop rotations reduced data variability. Compared to crops, the coefficient of variation of total nitrogen input decreased by almost 10% in crop rotations. Farmers somewhat intentionally varied application of organic and inorganic fertiliser from one season to another. Over the year, however, they accounted for variation in seasonal applications, as variability of input in crop rotation was again reduced. Hence, crop rotations brought a temporal component to the management of nutrient flows. Additionally, these spatially explicit crop rotations could bridge important gaps in understanding farm nutrient management and contribute to improving modelling of nutrient balances at different spatial scales.

Chapter 4

Upscaling land cover/land use pattern by means of remote sensing

Chapter 4.1

Mapping urban and peri-urban agriculture using high spatial resolution satellite data*

* This chapter is based on:
Forster, D., Buehler, Y., Kellenberger, T. W., 2009. Mapping urban and peri-urban agriculture using high spatial resolution satellite data. Journal of Applied Remote Sensing, Vol. 3, 033523 [doi:10.1117/1.3122364]

Abstract

In rapidly changing peri-urban environments where biophysical and socio-economic processes lead to spatial fragmentation of agricultural land, remote sensing offers an efficient tool to collect land cover/land use (LCLU) data for decision-making. Compared to traditional pixel-based approaches, remote sensing with object-based classification methods is reported to achieve improved classification results in complex heterogeneous landscapes. This study assessed the usefulness of object-based analysis of Quickbird high spatial resolution satellite data to classify urban and peri-urban agriculture in a limited peri-urban area of Hanoi, Vietnam. The results revealed that segmentation was essential in developing the object-based classification approach. Accurate segmentation of shape and size of an object enhanced classification with spectral, textural, morphological, and topological features. A qualitative, visual comparison of the classification results showed successful localisation and identification of most LCLU classes. Quantitative evaluation was conducted with a classification error matrix reaching an overall accuracy of 67% and a kappa coefficient of 0.61. In general, object-based classification of high spatial resolution satellite data proved the promising approach for LCLU analysis at village level. Capturing small-scale urban and peri-urban agricultural diversity offers a considerable potential for environmental monitoring. Challenges remain with the delineation of field boundaries and LCLU diversity on more spatially extensive datasets.

Keywords: Hanoi, land cover/land use, object-based classification, Quickbird, remote sensing, urban and peri-urban agriculture, VHR data, Vietnam

1 Introduction

The world population is increasing more rapidly than ever before. Particularly in Africa and Asia, the urban population is expected to nearly double by 2030 (UNFPA, 2007). Rural-to-urban migration contributes to urban sprawl and uncontrolled peri-urban land development with complex structures marked by a predominantly horizontal expansion (Kombe, 2005). Neglecting topological relationships and underlying biophysical and socio-economic processes may lead to spatial fragmentation and unsustainable urban land development (Carsjens and Van der Knaap, 2002). Fast assessment and monitoring of LCLU is thus essential to obtain a database for decision making in rapidly changing environments.

Remote sensing can supply information on land cover for mapping urban land use. Optical imaging satellite sensor systems such as Landsat or SPOT, work at a spatial resolution of 5–15 m (panchromatic bands) and 10–30 m (multi-spectral bands). Ikonos or Quickbird, the latest sensor systems, provide high to very high spatial resolution data with submeter resolution for the panchromatic band, and a 2–4 m spatial resolution for multi-spectral bands. But high or very high-resolution sensors lead to noise in generally homogeneous classes as the data contains increased information with more internal variability (Schiewe and Tufte, 2002; Schiewe et al., 2001). Traditional, pixel-based classification approaches are limited as regards the analysis of heterogeneous landscapes and lead to the reported ‘salt and pepper’ results (Aplin et al., 1999; Blaschke et al., 2000; Lu and Weng, 2007b). Thus, land cover/land use classification accuracy of high spatial resolution satellite data with traditional pixel-based classification methods is usually insufficient (Leukert, 2002; Schiewe and Tufte, 2002). This has led to the development of object-based classification methods using a segmentation approach prior to classification (Baatz and Schaepe, 2000; Benz et al., 2004). Shape, texture, neighbourhood relationships, digital elevation models, and GIS data can be used in addition to panchromatic and multi-spectral data to build semantic network structures for classification purposes.

Object-based classification using high spatial resolution data has been successfully applied to studies in agriculture (Buehler et al., 2007) and environmental monitoring (Jansen et al., 2006) and offers a promising tool for analysis of urban and peri-urban environments. Compared to rural areas, urban and peri-urban farm structures are, however, small and cropping patterns diversified. Crops can be highly diverse and multi-seasonal cropping is often practised, thus leading to continuous cropping patterns with no distinct start or end of a season. While a specific crop is being planted on one field, the same crop is already maturing on a neighbouring plot. The challenges of remote sensing in urban and peri-urban agriculture are thus seen as a reflection of the small-scale diversity in the classification result.

Crop, field size and location are, *inter alia*, factors driving farmers' decisions with regard to resource use (e.g. fertiliser management). Therefore, identification of crops and cropping area are important steps in assessing the prevailing farming systems. Segmentation, producing homogeneous objects with distinct crop characteristics, facilitates the classification process. However, if segmentation produces objects with characteristics that belong to more than one class, subsequent classification becomes a challenge. Development of a segmentation procedure to obtain homogeneous and optimally sized segments requires experience and knowledge of local LCLU.

This research assesses the potential of high spatial resolution satellite data to characterise urban and peri-urban agriculture. Particular focus is placed on determining the segmentation approach required to best address the management units (e.g. field or cropped land) of the different crops cultivated, and on evaluating suitable features for identification.

2 Materials and Methods

2.1 Study area

This study focuses on the district of Dong Anh (21° 8′ 14′′ N; 111° 49′ 44′′ E), north of the capital Hanoi, Vietnam. The site studied covers a subset of the Vinh Ngoc municipality (Fig. 1) spreading over an area of about 1.9 km2. It comprises both a built-up/residential area and agriculture land, the latter amounting to 75% of the subset area. Elevation ranges between 8–12 m above sea level. Most people practise mixed farming including crop and livestock production. The average farm size is around 0.22 ha. Two staple food crop and one cash crop season dominate annual production. The first season starts after the lunar New Year in mid-February and ends at the beginning of June, the second season starts shortly thereafter in mid-June and ends in mid-October. The first and second season are both characterised by a monsoon climate with heavy rainfall. The third season, covering the months of mid-October to beginning of February is, however, characterised by a temperate climate with only few showers. Rice paddy (*Oryza sativa*) is the main crop planted during the first and second season. Fields on slightly elevated terrain are also frequently cropped with maize (*Zea maize*) or sweet potato (*Ipomoea batatas*). Unlike the first and second season, the third growing season is far more diverse as farmers plant alternately maize, sweet potato or vegetables on a reduced area; an indication that much of the land remains fallow in winter. Aside from annual crops, a sizeable area is reserved for perennials, such as peach trees (Prunus sp.), star fruit (*Averrhoa carambola*), longan (*Dimocarpus longan*), lychee (*Litchi chinensis*), mango (*Mangifera domestica*), sapodilla (*Manilkara zapota*) or banana (*Musa sp.*).

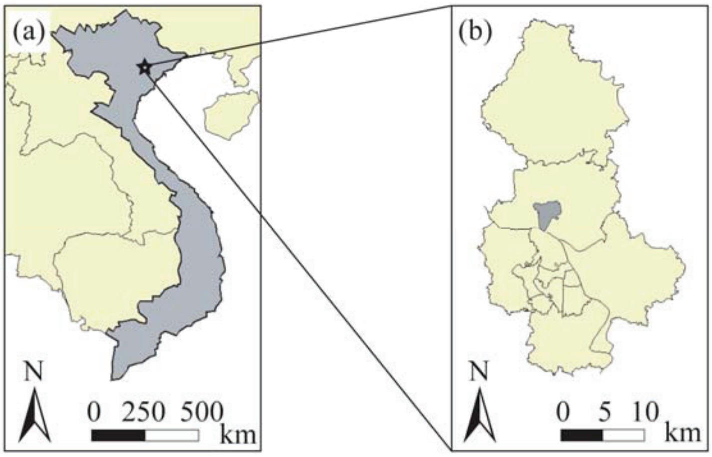


Fig. 1. Vietnam with its capital Hanoi (a), Hanoi province with its districts and Vinh Ngoc municipality (b).

2.2 Satellite data

Despite an early tasking request and a prolonged tasking period (Oct. 2006 – Jan. 2007), a new Quickbird satellite image was not acquired for reasons of higher priority orders. Thereafter, an archived Quickbird image (acquisition date 8th Dec. 2004), with a panchromatic band of 0.6 m and four spectral bands of 2.4 m spatial resolution was ordered for the Dong Anh district. The panchromatic band was scaled to 0.5 m and the multi-spectral bands to 2 m spatial resolution. Because elevation differences and atmospheric variability across the scene are expected to be minimal, and multi-temporal analyses were not planned, radiometric corrections were not applied to the imagery. The satellite data was geo-referenced using a second order polynomial transformation and in-situ GPS measurements (Chapter 2.3).

Furthermore, the widely used Normalised Difference Vegetation Index (NDVI) was computed (Rouse et al., 1973) for analysis of vegetation activity (Jiang et al., 2006; Lee et al., 2002; Pettorelli et al., 2005; Southworth et al., 2004).

2.3 Test data and evaluation

Extensive field data was collected during two farming system surveys (Oct. 2005 – Jan. 2006, Oct. 2006 – Jan. 2007) to identify patterns of crop and resource use. This period covers the third production season (i.e. cash crop season) and was selected due to the high LCLU diversity. Ground control points were measured with a differential GPS. Data on road infrastructure was collected in the municipality for satellite data geo-referencing. Agricultural data on LCLU, including field/plot position and shape, were also collected.

For lack of concurrent satellite data on the periods of the farming system survey, the ordered Quickbird image (acquisition date 8th Dec. 2004) was interpreted on the basis of expert knowledge and visual interpretation. The same Quickbird scene was thus used for classification and accuracy assessment. Since accuracy assessment was not entirely based on independent data, a certain risk prevails related to experts' misinterpretation. However, for lack of actual village data (i.e. parcel-bound data), the approach chosen seems the most effective, as the farming system survey allowed to study LCLU throughout the village.

Interpreted image data is subsequently referred to as test data (Tso and Mather, 2001). In the case of training samples, an operator's purposive selection of test data was chosen. Test data for accuracy assessment (i.e. reference data) was, however, retrieved by a stratified random selection process, where 50 additional objects were randomly selected for each class minus the training samples (Durrieu et al., 2008).

The LCLU classification result was finally subjected to an error matrix where the classification result was compared with reference data. Only agriculturally relevant classes were included in the accuracy assessment. Aside from the overall accuracy obtained by dividing the sum of correctly classified objects by the total number of sampled objects, additional indices such as 'kappa coefficient' and the class specific producer and user accuracy were calculated. According to (Tso and Mather, 2001), producer accuracy is calculated by dividing the number of correct objects of a specific class by the actual number of reference data objects for that class. User accuracy is however determined by dividing the number of correct objects of a specific class by the total number of objects assigned to that class. Producer accuracy informs about the proportion of correctly labelled objects in the reference data. This is also a measure of omission errors. User accuracy, however, quantifies the proportion of objects assigned to a specific class that agree with objects in the reference data. User accuracy indicates the probability that a specifically labelled object also belongs to that specific class in reality. It reveals commission errors.

2.4 Classification nomenclature

The LCLU classification nomenclature follows a hierarchical classification with two classes 'water' and 'land' on level 1 (Fig. 2). On level 2, land was subdivided into 'built-up&residential' and 'agriculture'. On classification level 3, agriculture was subdivided into seven classes. The 'water' and 'built-up&residential' classes were not further subdivided on level 3.

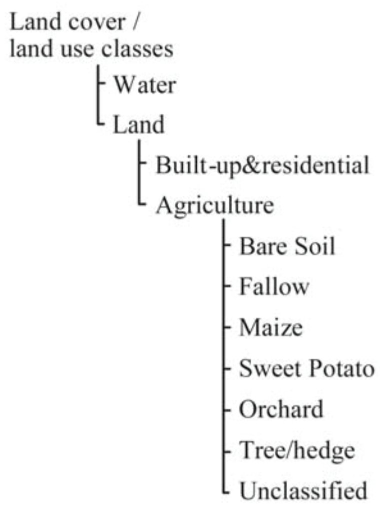


Fig. 2. Nomenclature of land cover/land use classes used in the study.

2.5 Multi-resolution segmentation

The object-based image analysis software Definiens Professional® was used for this study. Object-based image analysis consists of labelling homogeneous pixel groups (i.e. objects/segments). The input data first undergoes a segmentation process, which is based on the hypothesis that neighbouring image pixels belong to the same object. Neighbouring pixels are merged and grouped depending on homogeneity parameters (Schiewe and Tufte, 2002). The different input bands can be weighted and their information added to the image objects. A scale parameter, determining the maximum allowed heterogeneity for the image object, influences segment size. This implies, for instance, that at a given scale heterogeneous data will result in smaller objects than homogeneous data. Variation of the scale parameter value allows the user to build an image object hierarchy consisting of two or more levels. Every image object of a lower level is assigned to a super-object on the next higher level (Definiens, 2006).

Table 1. Segmentation levels and weight settings.

Segmentation level	1	2	3	4
Blue band	1	1	1	1
Green band	1	1	1	1
Red band	1	1	1	1
Near infrared band	6	6	4	4
Panchromatic band	1	1	12	12
Scale parameter	800	260	40	3
Colour/Shape	0.9/0.1	0.9/0.1	0.5/0.5	0.8/0.2
Compactness/Smoothness	0.5/0.5	0.5/0.5	0.8/0.2	0.8/0.2

In this study, four segmentation levels were computed based on four multi-spectral and one panchromatic band (Table 1). Appropriate selection of band weights and segmentation parameters requires experience and knowledge of local LCLU. Due to the small-scale diversity of peri-urban agriculture, the panchromatic band with 0.5 m spatial resolution played the essential role in segmentation. Also the near infrared band, used to compute the NDVI, was preferred and weighting was higher than for the remaining bands. In a first step, segmentation of levels 1 and 2 aimed at large, homogenous image objects of 'water', 'land' and 'built-up&residential', achieved by a six-fold weighting of the near infrared band and high scale parameters. Conversely, for analysis of the fine-structured, diversified 'agriculture' on level 3, weighting and segmentation parameter settings were adjusted to cope better with heterogeneity. In addition to a moderate scale parameter, a twelve-fold weighting of the panchromatic and a four-fold weighting of the near infrared band produced segments comparable to size and shape of management units (e.g. fields or cropped land). Segmentation level 4 was specially prepared for sub-object analysis by means of texture features. The scale parameter was further reduced and a twelve and four-fold weighting of the panchromatic and near infrared band, respectively was applied. Colour/shape and compactness/smoothness criteria were adjusted iteratively. To create meaningful objects, 'colour' was most important and weighting was maximised on segmentation levels 1 and 2. On level 3 more weight was placed on the 'shape' to enhance delineation of the field objects. On level 4, 'colour' weighting was again preferred. As the compactness/smoothness criterion depends on 'shape', it will gain more influence the higher the shape criterion. On level 3, higher 'compactness' slightly improved the overall compactness of field objects.

2.6 Labelling by membership functions

On segmentation level 3, main focus was placed on classification of the agricultural area according to the class nomenclature described in Fig. 2. The classification approach Definiens Professional allows the use of a multitude of membership functions to separate image objects at specific segmentation levels (Table 2).

These membership functions can be broadly classified as spectral, textural, morphological, and topological features. The term 'texture' refers to the variation in the grey values of adjacent pixels and their specific spatial arrangement. At the field object level, texture allows the user to characterise within-field variation due to different cultivation strategies. As integrated in the software, texture features take into account the structure elements of an image object (e.g. shape or number of sub-objects). The textural feature 'density of sub-objects (mean)', for instance, calculates the mean value from the density of the sub-objects. Thereby, density is expressed by the area covered by an image object divided by its embedded radius (Definiens, 2006). Conversely, morphological features analyse the shape of an object (e.g. 'length/width'), whereas topological features relate the position of an object to another in the spatial context (e.g. 'relative border to'). In general, a systematic approach to segmentation and careful selection of features are necessary to achieve a reasonable LCLU classification. Because of its ability to indicate vegetation activity, the NDVI index was calculated and widely used in addition to other features available in the software.

Table 2. Overview of features used to separate land classes.

LCLU class and segmentation level	NDVI[1]	Mean of blue band[1]	Mean of NIR band [1]	Mean of pan band [1]	Max. diff. of pan band [1]	Mean sub-objects: Stdv. pan[2]	Area sub-objects: mean[2]	Density of sub-objects: mean[2]	Area[3]	Length/width[3]	Existence of super-objects[4]	Thematic object ID[4]	Rel. border to[4]	No rel. border to[4]	Classified as[4]
Water (1)			X												
Land (1)			X												
Built-up/residential (1)	X			X			X								
Water (2)		X	X						X	X			X		
Land (2)		X	X						X	X			X	X	
Built-up/residential (2)	X			X			X				X				
Land (3)												X			
Built-up/residential (3)												X			
Agriculture (3)												X			
Fallow (3)	X			X									X		
Bare soil (3)	X		X												
Maize (3)	X				X			X		X			X		
Sweet potato (3)	X														
Orchard (3)						X	X		X	X					
Tree/hedge (3)						X	X		X	X				X	
Unclassified (3)															X

Features: [1]spectral, [2]textural, [3]morphological, [4]topological

3 Results and Discussion

3.1 Segmentation and classification of 'water' and 'built-up&residential'

Objects labelled as 'water' and 'land' were mainly separated by spectral characteristics. Segmentation with focus on spectral bands resulted in large and clearly classified image objects. As water is a main absorber of sunlight, especially in the near infrared region, water showed rather low NIR values compared to land. Water was therefore mainly classified with a low mean value of the NIR band (Fig. 3). Moreover, indirect features like 'mean of blue band', 'length/width' and 'maximum area' were used to identify the remaining water objects.

Buildings and roads reflect sunlight well but are intersected by gardens and shadows, which reflect sunlight only to a minor extent. This resulted in heterogeneous objects with complex shapes and a high standard deviation in the panchromatic band. This information was subsequently used together with the 'NDVI' and 'area of sub-objects (mean)' to separate the 'built-up&residential' class from agriculture. To avoid conflicts resulting from insufficient segmentation of agricultural areas, the classes 'water' and 'built-up&residential' were subsequently masked out and excluded from the classification process.

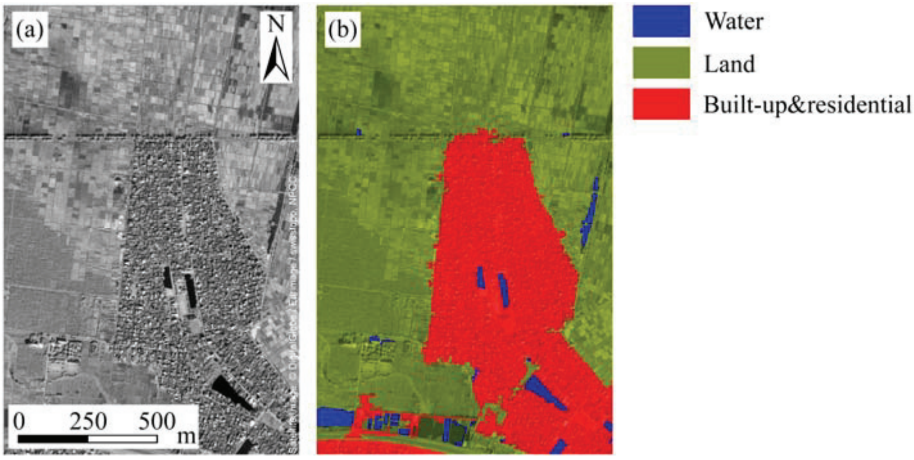


Fig. 3. Classification on segmentation level 2,
panchromatic band (a) and classification result (b).

3.2 Segmentation and identification of 'agriculture'

In this study, 'agriculture' was defined as land, excluding LCLU classes such as 'water' and 'built-up&residential'. Segmentation and identification of 'agriculture' was a challenge due to the number of sub-classes to be identified. Large image objects of 'agriculture' on segmentation levels 1 and 2 insufficiently captured the local crop diversity. Thus, segmentation of the 'agriculture' class on level 3 was meant to generating image objects with dimensions similar to those of the fields. Best results were obtained by a high weighted panchromatic band with clearly visible field boundaries at pixel resolution. However, object size and shape generally proved to be unsatisfactory as field boundaries were not fully reproduced (Fig. 4). On the other hand, image objects consisted partially of more than one field and object characteristics were not entirely crop or field specific. Consequently, the LCLU classification presented a challenge due to the mixed objects partially containing information from several fields or crops.

The class ‘bare soil’ was defined as ploughed soil without any vegetation cover. First, morphological and textural features were used to derive the structure of ploughed fields, easily visible at pixel resolution on the panchromatic band (Fig. 5). Nevertheless, the results were insufficient. As segmentation was too coarse, only a few of the length structures were transformed into longish segments. The ‘length/width’ and density of the ‘sub-objects (mean)’ did not change substantially, hence, they were not used for labelling. However, the missing vegetation cover resulted in low NIR and NDVI values, which were subsequently used to classify ‘bare soil’.

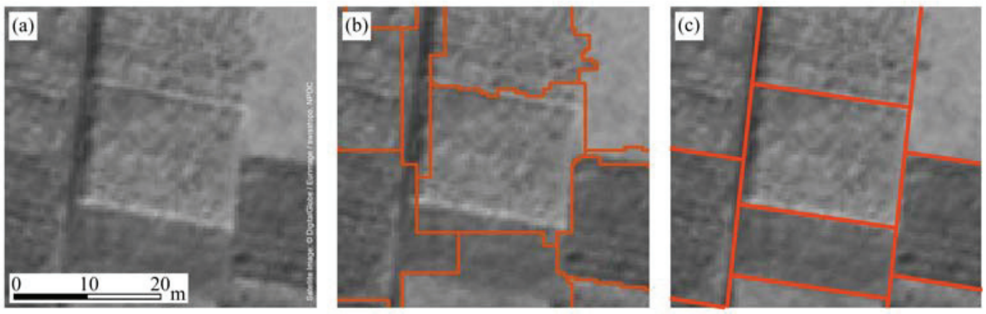


Fig. 4. Segmentation example on level 3. Panchromatic band (a), segments based on the algorithm implemented in the software (b) and segments outlined by visual interpretation and GIS (c).

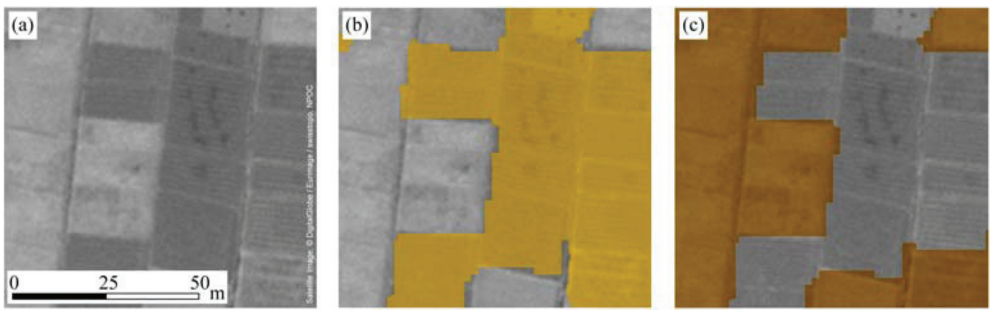


Fig. 5. Classification example. Panchromatic band (a), ‘bare soil’ (b) and ‘fallow’ classes (c).

The ‘fallow’ class consisted of empty fields (i.e. no crops) with some vegetation cover from spontaneous growing or remaining crop residues. The characteristics of ‘fallow’ varied widely. Geometric patterns such as length structures were missing and ‘fallow’ fields had a lower NDVI value than planted fields but higher than fields with ‘bare soil’. Furthermore, ‘fallow’ fields had higher pan values than those of ‘bare soil’. The higher values of the panchromatic band were subsequently used as an additional feature to separate fallow land from bare soil.

Maize was predominantly cultivated in places where soil characteristics and water availability favoured its growth. This practice led to maize production clusters. As with other winter crops, the maize cropping period could start at any time as long as the crop matured before the beginning of the first production season (i.e. paddy season) in mid-February. Maize was therefore encountered at different phenological stages, leading to varying textural characteristics (Fig. 6): at the stage of stem elongation, heading and flowering, it had strong uprising leaves and a closed canopy. At fruit development, ripening and senescence, however, maize developed more bended and hanging leaves with a more open canopy, thus resulting in more and smaller sub-objects. Compared to maize at the stage of stem elongation, heading and flowering, the feature ‘density of sub-objects (mean)’ was thus reduced and used in a stepwise classification procedure.

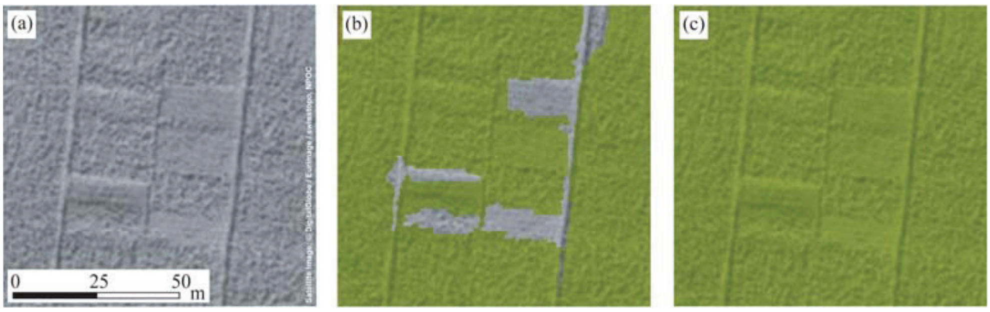


Fig. 6. Example of stepwise classification. Panchromatic band (a) and the ‘maize’ class before (b) and after (c) adjustment of the feature ‘density of sub-object (mean)’.

Sweet potato was grown on different soil types. Maize-cultivated soils were also suitable for sweet potato and alternately used for its cultivation. Leaf production was favoured (pig feeding) and boosted with high nitrogen applications, leading to a dense and often completely closed canopy with high to very high NDVI values. Vegetation was so dense that furrows were almost invisible. Thus ‘sweet potato’ was classified by a high NDVI value.

The orchards grew peaches, mangoes, star fruit, longans, lychees, and sapodillas. Peach trees, cultivated for ornamental flower production, were rather small and had crowns of about 1–1.5 m diameter. All the other trees were of varying size with 3–10 m crown diameters. Trees of ‘orchard’ did not appear as single trees but always in stands with a typical texture. The 'orchard' trees revealed a geometric cultivation pattern (e.g. line, chessboard). Depending on planting distance and tree age, they could be distinguished at pixel resolution and formed separate objects on segmentation level 4. Textural and morphological features were therefore used to classify 'orchard'. But separability was barely sufficient, as interference was observed with the 'tree&hedge' and 'maize' classes.

Trees of the 'tree&hedge' class were detected along roads (avenues) or as hedges separating different fields or built-up and residential areas. Though geometric patterns were missing, the spectral characteristics were similar to 'orchard' and thus difficult to separate. The objects of the class 'tree&hedge' were, however, smaller (single trees) or had a higher 'length/width' feature value. Aside from morphological features, textural and topological features with adjusted feature ranges were used to separate the 'tree&hedge' class.

3.3 Classification accuracy

The results were verified qualitatively and quantitatively. Apart from a few exceptions, the qualitative, visual comparison of the LCLU map with the panchromatic band of Quickbird satellite data revealed successful localisation and identification of the classes (Fig. 7). A classification error matrix was computed for quantitative accuracy assessment (Table 3). For lack of additional satellite data, concurrent with the periods of the field surveys, a reference dataset was generated based on the ordered Quickbird satellite data and expert knowledge. The overall accuracy was 67%, while the kappa coefficient had a value of 0.61. The class-specific producer accuracy varied between 94% for 'bare soil' and 61% for the 'tree&hedge' class. User accuracy reached the highest value of 92% for the 'sweet potato' class. Lowest values were obtained for the class 'orchard' with 47%. A noticeable feature is the significantly varying producer and user accuracy. The range between producer and user accuracy was wide for classes such as 'fallow', 'bare soil', 'orchard' or 'maize' compared to the rather narrow range of other classes (e.g. 'sweet potato'). These differences were partly attributed to omission and commission errors, as the date of satellite and field data collection differed. Moreover, the moderate segmentation results also affected classification, as mixed objects were labelled to the wrong LCLU class.

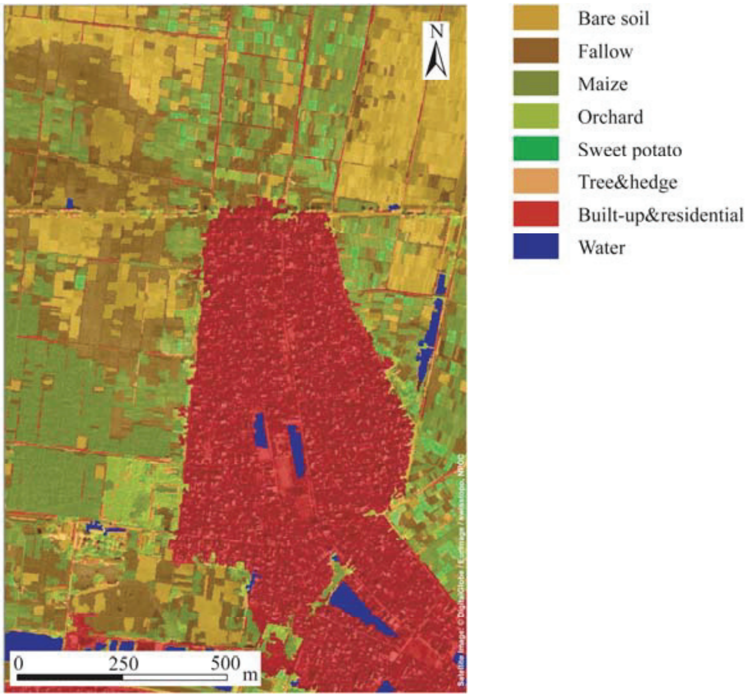


Fig. 7. Classification results and corresponding class nomenclature.

Table 3. Classification error matrix, comparing objects of different classes based on test data.

Classified data	Test data (reference)								
	Bare soil	Fallow	Maize	Sweet potato	Orchard	Tree/ hedge	Prod. acc. (%)	User acc. (%)	Class kappa coefficient
Bare soil	33	15	0	0	0	2	94.3	66.0	0.62
Fallow	1	40	2	1	4	2	47.1	80.0	0.72
Maize	0	15	27	4	1	4	73.0	52.9	0.46
Sweet Potato	0	0	2	46	0	2	80.7	92.0	0.90
Orchard	0	10	3	2	24	11	72.7	48.0	0.42
Tree/Hedge	1	5	3	4	4	33	61.1	66.0	0.59
Overall accuracy (%)				67.4	Overall kappa coefficient				0.61

4 Conclusion

This study investigated the potential of an object-based classification method for high spatial resolution data in urban and peri-urban agriculture, which may provide a database for decision making on land use. Object-based classification offers many useful features (e.g. spectral, textural, morphological, and topological) for classification. Insufficient segmentation limits, however, the potential of these features. Despite a newly segmented subset after classification of ‘water’ and ‘built-up&residential’, the new segmentation process was still insufficient and objects, accentuating size and shape of fields, were only partially reached. Even a high weighting of the panchromatic band did not allow extraction of visually distinctive field boundaries. Instead, a large proportion of objects were made from more than one field. The segmentation process is therefore considered to be very decisive and crucial for successful discrimination, especially with regard to land cover/land use classification at field parcel level. To overcome insufficient segmentation, filters could also be used to extract distinctive objects, such as field boundaries or streets on the panchromatic and multi-spectral bands. For instance Karantzalos and Argialas (2002) reported on the usefulness of high-pass filters to detect man-made objects and linear features in anthropogenic environments. The filtered bands could be subsequently reused in the segmentation process.

Classification has to be evaluated as regards the moderate segmentation results. While some classes revealed low producer or user accuracy, the overall accuracy of 67% was still above average and the kappa coefficient provided good classification results. The relatively good results were explained by the fact that the accuracy assessment was based on image objects. The object as a whole was classified/evaluated based on the dominant LCLU. Neither classification nor accuracy assessment (i.e. reference data preparation) addressed the issue of objects made from more than one field. With other words, the classification results are good, but they do not fully reflect classification accuracy at the management unit level (e.g. field or cropped land).

Nevertheless, LCLU segmentation and classification of urban and peri-urban agriculture of Hanoi proved satisfactory. Method and data can be recommended for overview and assessment of land cover/land use at village level, where field parcel bound information is not stringent. However, research with focus on field boundary delineation could contribute to improve LCLU classification at field parcel level. As well the use of considerably larger datasets (i.e. more spatially extensive) is recommended to test the suitability of object-based classification in more complex peri-urban environments.

Chapter 4.2

Mapping diversified peri-urban agriculture – Potential of object-based versus per-field land cover/land use classification*

* This chapter is based on:
Forster, D., Buehler, Y., Kellenberger, T. W., Lennartz, B., 2009. Mapping diversified peri-urban agriculture – Potential of object-based versus per-field land cover/land use classification. Geocarto International, 99999:1 [doi: 10.1080/10106040903243416]

Abstract

Availability of high spatial resolution satellite image data contribute to improving land cover/land use (LCLU) classification in agriculture. Since successful classification of crops is greatly influenced by field boundary delineation accuracy, a classification procedure based on Quickbird satellite image data was developed and tested in this study to enable LCLU mapping of highly diversified peri-urban agriculture at sub-communal and communal level (7 km2). Segmentation performance of the panchromatic band in combination with high pass filters (HPF) was tested first. Accuracy of field boundary delineation was then evaluated by an object-based segmentation, a per-field and a manual classification, along with a quantitative accuracy assessment. Classification on sub-communal level revealed an overall accuracy of 84% with a kappa coefficient of 0.77 for the per-field vector segmentation compared to an overall accuracy of 56–60% and a kappa coefficient of 0.37–0.42 for object-based approaches. Per-field vector segmentation was thus superior and used for LCLU classification at communal level. Overall accuracy scored 83% and the kappa coefficient 0.7. In small-scale, intensified agricultural systems, such as in peri-urban areas, per-field vector segmentation and classification achieved yet higher classification results. Successful field boundary delineation algorithms could significantly improve object-based classification. Use of data from airborne digital sensors or airborne laser scanners are suggested to further improve field boundary delineation and crop discrimination.

Keywords: field boundary, high-pass filter, high spatial resolution satellite data, object-based classification, per-field classification

1 Introduction

Peri-urban agriculture is an important provider of fresh food to the urban market. Especially in developing and emerging countries, peri-urban landscapes are generally heterogeneous and characterised by their temporal variability in cropping patterns, small-scale fields and fast changes due to the urban vicinity (Smit et al., 1996). However, peri-urban production areas are increasingly under pressure from rural-to-urban migration and uncontrolled peri-urban land development (Midmore and Jansen, 2003; Vagneron, 2007). Rapid and accurate assessment of land cover/land use (LCLU) would therefore be a better approach to highlight the importance of peri-urban production and improve land development and planning.

Selection of remote sensing data for LCLU analysis should include the required spatial resolution based on variations of the study environment. For instance, where spatial variation of a landscape can be expected within 250–300 m distance, Enhanced Thematic Mapper (ETM) or Thematic Mapper (TM) data may be used for LCLU analysis (Aplin and Atkinson, 2004). However, in any spatial resolution, a decreasing field parcel size will increase the number of mixed pixels in the border zone, reported as a major problem in per-pixel classification of high spatial resolution images (Aplin, 2006; Cracknell, 1998; Fisher, 1997; Lu and Weng, 2007a). In contrast, high spatial resolution data contains more detailed information and allows to reduce markedly mixed pixels. However, if land cover variation is expected within 5–15 m, such as in small-scale peri-urban agriculture, mixed pixels may also become an issue in high spatial resolution data. The number of mixed pixels increases with decreasing field size especially in the border zone of field parcels. Furthermore, high spectral variation within the same LCLU type may pose a challenge to classification (Cushnie, 1987; Irons, 1985). Increased spectral variation is closely associated with the degree of spectral heterogeneity (Lu and Weng, 2007a). Spectral variation will increase with spatial heterogeneity or spatial variation. The larger the observation area and the smaller the size of the pixels investigated, the greater the spatial heterogeneity and the degree of spectral heterogeneity.

In data analysis (i.e. classification), the image data is pre-processing by radiometric and geometric correction, as well as image registration (e.g. geo-referencing). Geometric enhancement helps to highlight the required information content by smoothing image areas or detecting and enhancing edges and lines for example. Different studies reported the usefulness of high-pass filters (HPF) to detect linear features. Karantzalos and Argialas (2002) used HPF to detect man-made objects and linear features in anthropogenic environments, such as coast lines, roads and parcel boundaries. For data fusion of imagery over predominantly agricultural areas, HPF was also favoured as pre-processing step (Ahmad and Singh, 2002; Chavez Jr. et al., 1991; Ray, 2004; Wang et al., 2005; Wenbo et al., 2008). Thus, application of HPF prior to classification is expected to improve classification results.

Classification of pre-processed image data is either performed by the common pixel-based, the per-field or the more recent object-based classification approach. In heterogeneous, complex landscapes, per-pixel classification of high spatial resolution data may cause scattered 'salt and pepper'-like results due to high spatial frequency (Aplin et al., 1999; Lu and Weng, 2007a; Rydberg and Borgefors, 2001; Wu et al., 2007). Conversely, per-field and object-based classification approaches are based on image data segmentation into 'objects', followed by a labelling procedure (Baatz and Schaepe, 2000; Benz et al., 2004). Therefore, within-field variation is mostly removed and classification accuracy increased (Aplin and Atkinson, 2004; Aplin et al., 1999; Dean and Smith, 2003; Pedley and Curran, 1991). Because of the inherent and scattered parcel structure of agricultural landscapes, per-field and object-based classification techniques are favoured methodologies to map agricultural land cover with image data (Dean and Smith, 2003). An additional convincing argument is the fact that crop management decisions and agricultural statistics are taken on a per-field basis. Per-field and object-based classification approaches differ solely by the segmentation step. In per-field classification, per-field vector and raster data are manually merged in a geographical information system (Aplin and Atkinson, 2001; Dean and Smith, 2003; Erol and Akdeniz, 2005; Janssen and Molenaar, 1995; Wu et al., 2007), while the automated segmentation procedure replaces manual per-field delineation in object-based classification (Benz et al., 2004; Walter, 2004). The subsequent classification procedure (e.g. labelling) relies on spectral, textural, morphological or topological information of the objects.

Automated segmentation of field patterns has been the focus of research for the last two decades (Benie and Thomson, 1992; Chen et al., 2006; Janssen and Molenaar, 1995; Munoz et al., 2003; Rydberg and Borgefors, 2001). Accurate field boundary delineation is a prerequisite for successful per-field/object-based classification. But spectral and spatial properties of remote sensing data, as well as variation in field size and shape complicate automatic field boundary delineation. For instance Rydberg and Borgefors (2001) note that variation between fields is not always apparent, and the within-field variation may be higher than the variation between-fields. Mueller *et al.* (2004) further refer to three main challenges when segmenting agricultural landscapes; (i) numerous small objects may lead to high grey value variation and over-segmentation, (ii) the low contrast between objects results in under-segmentation and (iii) deviation from rectangular shapes prevents the use of fixed geometric rules. Data processing with HPF increases the contrast between fields and may thus improve automated segmentation and subsequent classification of agricultural landscapes.

This study addresses the development and analysis of a segmentation and classification approach at sub-communal and communal level for high spatial resolution satellite data to map LCLU of highly diversified peri-urban agricultural landscapes. The following hypotheses were proposed: (i) use of pre-processing techniques (i.e. HPF) and multi-resolution region growing on panchromatic Quickbird satellite image data improve field boundary delineation, (ii) the LCLU classification results obtained by object-based classification are comparable to those of the per-field classification methodology and (iii) combined elements of object-based and per-field classification techniques allow successful classification of LCLU throughout the communal level.

2 Data Sources

2.1 Study area

This study focuses on the Bac Hong commune (21° 10′ 36′′ N; 105° 48′ 36′′ E), north of the capital Hanoi, Vietnam (Figure 1). The Bac Hong commune comprises the six villages of Ben Chung, Minh Hoi, Phu Liem, Quan Am, Thuong Phuc, and Thuy Ha. They cover an area of about 7.2 km^2, whose elevation ranges from 8–12 m above sea level. Most of the area consists of flat, built-up and diversified, small-scale peri-urban agriculture fields of 80–600 m^2 size (average 350 m^2). Recent economic development and a neighbouring urban market led to the emergence of a highly intensive system with cropping throughout the year. The first and second growing season (mid-February to end of May, mid-June to end of September) is dominated by rice paddy (*Oryza sp.*) and the third season (October to February) by maize

(*Zea maize*), sweet potato (*Ipomoea batatas*) and vegetables. Aside from annual crops, a sizeable area is reserved for perennial crops.

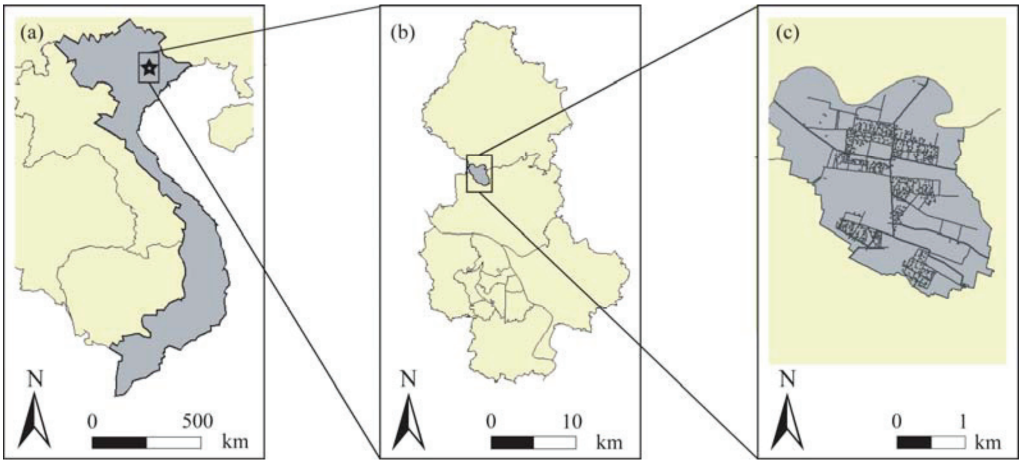


Figure 1. The country Vietnam (a) with the province Hanoi (b) and the commune Bac Hong (c).

2.2 Satellite and reference data

An archived high spatial resolution Quickbird satellite image (recording date 8 December 2004) was ordered for the Dong Anh district and the Bac Hong commune, respectively. Spatial resolution of the dataset for the panchromatic band was 0.6 m and 2.4 m for the four multi-spectral bands (DigitalGlobe, 2007). Data was resampled using a cubic convolution filter kernel. The panchromatic band was scaled to 0.5 m spatial resolution and to 2 m for the multi-spectral bands, respectively. Since multi-temporal analysis was not taken into account, radiometric correction was not applied. Due to the small elevation difference of up to 4 m, no significant illumination differences were expected and the atmospheric conditions were assumed to be constant. Rainfall ranged between 13 and 66 mm and temperatures between 17 and 20 °C for the months of November to February (HSO, 2004). Therefore, humidity was generally low and shortwave blurring was not observed in the Quickbird satellite image. The image was geo-referenced using a second order polynomial transformation considering ground control points. The latter were measured in situ with a differential GPS at well identifiable infrastructure elements evenly distributed over the entire communal area. Ground truth data on LCLU was collected with a differential GPS over two years (Oct. 2005–Jan. 2006 and Oct. 2006–Jan. 2007). Due to the different points in time of image acquisition and ground truth data collection, inspected LCLU was subsequently referred to as test data.

3 Methods

Development of an appropriate field boundary delineation approach is described in section 3.1. The most relevant features used for labelling (i.e. classification) are presented in section 3.2. The highest ranking delineation approach is subsequently scaled from sub-communal training area to communal level (section 3.3). In this study, segmentation and classification were performed with Definiens Professional®, and filtering with PCI Geomatica 10®. For all other vector work ArcGIS 9.1® was used.

3.1 Classification-based field boundary accuracy assessment

Accuracy of field boundary delineation is difficult to evaluate. The delineation process is usually assessed by a qualitative visual comparison. Visual interpretation is very helpful when assessing a few large fields. Nevertheless, with increasing area and decreasing field size, qualitative evaluation of field boundary delineation becomes difficult and requires quantitative accurate measurements. In classification-based field boundary accuracy assessment, automated segmentation (e.g. single-/ multi-resolution segmentation) is compared to per-field vector segmentation by classification and accuracy assessment based on an error matrix (Figure 2).

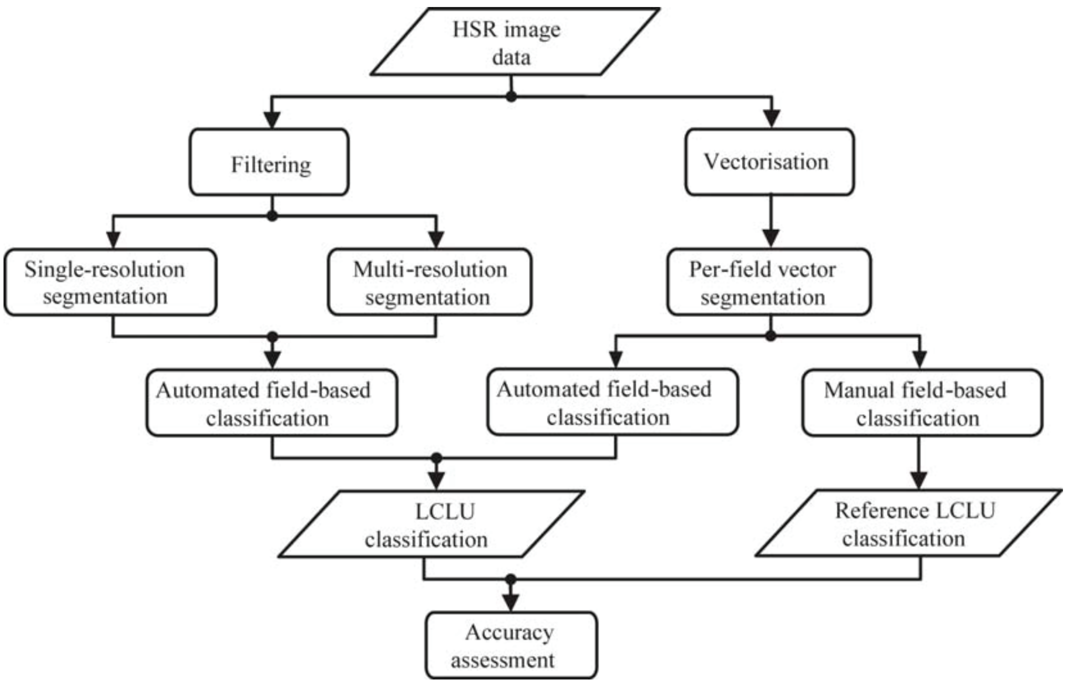


Figure 2. Schematic drawing of the classification-based field boundary accuracy assessment method.

The field boundary accuracy assessment was conducted based on an image subset of Quan Am village. The subset covering 19 ha of agricultural land is representative of the intensive vegetable cropping system of the commune. Previous tests revealed that multi-spectral bands did not improve segmentation in peri-urban agriculture. Due to the small-scale diversity of LCLU, field boundary delineation only used the (spatially best resolved) panchromatic band. For processing the satellite data in terms of improved delineation of single objects, two different HPF were applied to the panchromatic band: Laplace Type I with a weighted 3×3 filter window (0,1,0,1,–4,1,0,1,0) that sums up to zero and an edge sharpener, which uses a subtractive smoothing method to sharpen an image. The edge sharpener starts with an averaging filter, subtracts the averaged image from the input image and ends by adding the image difference back to the original.

Performance of the panchromatic band, edge sharpened band and Laplace filtered band for three different field boundary delineation approaches was subsequently evaluated. First, two types of segmentation were applied, i.e. 'single-resolution' and 'multi-resolution'. 'Multi-resolution' segmentation differs from 'single-resolution' by additional hierarchical resolution levels reported to improve field boundary delineation. A polygon per-field vector layer was then created by manual digitisation of field boundaries in GIS used for a per-field classification and considered as best ground reference.

The automated segmentation approaches were validated according to the procedure suggested by Benz *et al*. (2004), i.e. automated segmentation of 'single-' and 'multi-resolution' data is considered successful if the objects were congruent with those on the reference layer (i.e. per-field vector layer). In this case, automatically segmented and reference objects have similar spectral, textural and morphological properties and could be assigned to the same class using the same decision features. The panchromatic band, as well as the panchromatic and filtered band of 'single-' and 'multi-resolution' data were then classified (section 3.2). The same classification algorithm was also applied to the 'per-field vector' segmentation layer. Vegetable, maize, orchard, and fallow classes were used for LCLU analysis. Classification of the particular segmentation was then compared to a manual classification (reference) based on the 'per-field vector' segmentation. Quantitative assessment was performed by computation of an error matrix on a pixel basis (Tso and Mather, 2001) excluding built-up area, border zone and road infrastructure. Aside from the overall and average accuracy, the 'kappa coefficient' (Cohen, 1968) was also calculated.

3.2 Relevant features for labelling

The fuzzy classification approach applied allows the use of a multitude of membership functions to separate image objects into classes at specific segmentation levels (Table 1). Potential membership functions are based on spectral, textural, morphological, and topological features. The term 'textural' refers to the variation of grey level values of adjacent pixels and their specific spatial distribution. At field object level, the textural feature allows to characterise within-field variation caused by different cultivation strategies and takes into account the structure elements of an image object (e.g. shape or number of inherent sub-objects) within the selected strategy. The textural feature 'density of sub-objects (mean)', for instance, calculates the mean value from the density of the sub-objects. Thereby, density is expressed by the area covered by an image object divided by its embedded radius (Definiens, 2006). Texture can also be addressed by texture features according to Haralik (Definiens, 2006; Haralick, 1979; Haralick et al., 1973), such as 'Grey Level Co-occurrence Matrix (GLCM) entropy' and 'Grey Level Difference Vector (GLDV) angular second moment'. However, morphological features address the shape of an object (e.g. 'length/width'), whereas topological features relate the position of an object to another in the spatial context (e.g. 'relative border to'). Further features such as Normalised Difference Vegetation Index (NDVI) (Rouse et al., 1973) or primary and secondary features of filtered bands (i.e. Sobel Edge Detector and Laplace Types I) were also included. Multiple representative training areas in Thuy Ha, Thuong Phuc and Ben Chung village were used for steady adjustment of feature rules and ranges. The labelling algorithm scheme was developed based on the per-field vector segmentation and was then used in section 3.1 and 3.3.

3.3 Upscaling from sub-communal training area to communal level

Pre-processing of communal image data included preparation of filtered bands such as Sobel Edge Detector and Laplace Types I. As the per-field vector best addressed the field boundaries, a per-field vector layer was created for all six villages of the commune and served as thematic attribute for segmentation. The identical classification algorithm (section 3.2), developed for the classification-based field boundary accuracy assessment, was applied to all six villages. Classification accuracy was then assessed. Instead of a pixels comparison, a total of 500 field objects were selected randomly in class-proportional sampling to evaluate the classified LCLU (i.e. vegetable, maize, orchard, and fallow).

Table 1. Overview of features used to separate land classes.

Features	Vegetables	Maize	Orchard	Fallow
NDVI[1)]	x	x	x	x
Mean of panchromatic band [1)]		x	x	x
Mean of blue band[1)]	x	x	x	x
Mean of green band [1)]	x			x
Mean of NIR band [1)]		x		x
Mean of HPF band Laplass Type 1 [1)]	x	x		x
Mean of HPF band Sobel Edge Detector 1 [1)]	x	x	x	x
Stdv. of panchromatic band [1)]		x	x	x
Stdv. of blue band [1)]	x		x	
Stdv. of green band [1)]				
Stdv. of HPF band Laplass Type 1 [1)]	x	x	x	x
Stdv. of HPF band Sobel Edge Detector [1)]	x			x
Brightness [1)]	x			
Mean sub-objects: Stdv. pan [2)]			x	
Area sub-objects: mean [2)]			x	
Density of sub-objects: mean [2)]	x	x		
GLCM entropy [2)]		x		
GLDV angular 2nd moment [2)]		x		
Area [3)]			x	

Features: [1)]spectral, [2)]textural, [3)]morphological

4 Results

4.1 Accuracy of field boundary

Field boundaries were generally well identified by visual interpretation (Figure 3). If field boundary was not clearly distinguished, the crop provided approximate field size. The fields exhibited homogeneous or heterogeneous crop covers. The homogeneous crop cover comprised either no, well or evenly developed crop stands. Heterogeneous crop covers were unevenly developed or planted according to a particular cropping pattern (in rows and beds). With a well and evenly developed crop stand and neighbouring fields differing in terms of contrast and homogeneity (Figure 3a), segmentation on the panchromatic band yielded acceptable results and quite effective field identification. Use of filtered pan bands (i.e. edge sharpener and Laplace Type I) further improved the segmentation result and allowed complete field delineation. However, where within-field heterogeneity was increased, the segmentation result was rather poor (Figure 3b). Row cultivation led to a critical degree of contrast on the panchromatic band, which was further accentuated by the edge sharpener. The field as a unit was not identified; instead within-field structures were outlined. Additional use of Laplace Type I filtered band finally reduced within-field heterogeneity and slightly improved field boundary delineation. Where contrast to neighbouring fields was less pronounced (Figure 3c), the edge sharpener was not effective but Laplace Type I provided better segmentation results. Segmentation on the panchromatic band led to a meaningless object far from its actual field size or shape. In many cases, field boundary delineation was not sufficiently well addressed by segmentation on the pan or by additional use of the edge sharpener or Laplace Type I filtered band (Figure 3d).

Field boundary delineation was difficult despite the use of additional filtered bands. Though automated segmentation did not fully match the per-field vector, object properties may still fall within the fuzzy range of features used for classification. Figure 4 lists the classification results of the segmentation on the panchromatic band with additional use of the edge sharpener and Laplace Type I filtered bands. Furthermore, visual comparison of single (Figure 4a) and multi-resolution segmentation (Figure 4c) was possible with the per-field vector segmentation and the manually classified reference based on expert knowledge (Figure 4b). In general, single and multi-resolution segmentation shared many common objects assigned to the same LCLU class. Nonetheless, some differences prevail when comparing the panchromatic band, the panchromatic & edge sharpened and the panchromatic & Laplace Type I sharpened bands. The ‘maize’ class appeared to be more dominant in single and multi-resolution segmentation than in the reference. In contrast, the class ‘orchard’ was hardly present in single and multi-resolution segmentation; however, its presence was still considerable in the reference. The land labelled as ‘fallow’ and ‘vegetable’ appeared to be more or less within the same range as the reference. Overall, deviation of the objects from the per-field vector rendered visual comparison rather difficult. More meaningful was the comparison of the constant per-field vector classification with the reference (Figure 4b). Despite a few misclassified objects, many were correctly labelled, yet highlighting over-/underrepresented classes appeared difficult.

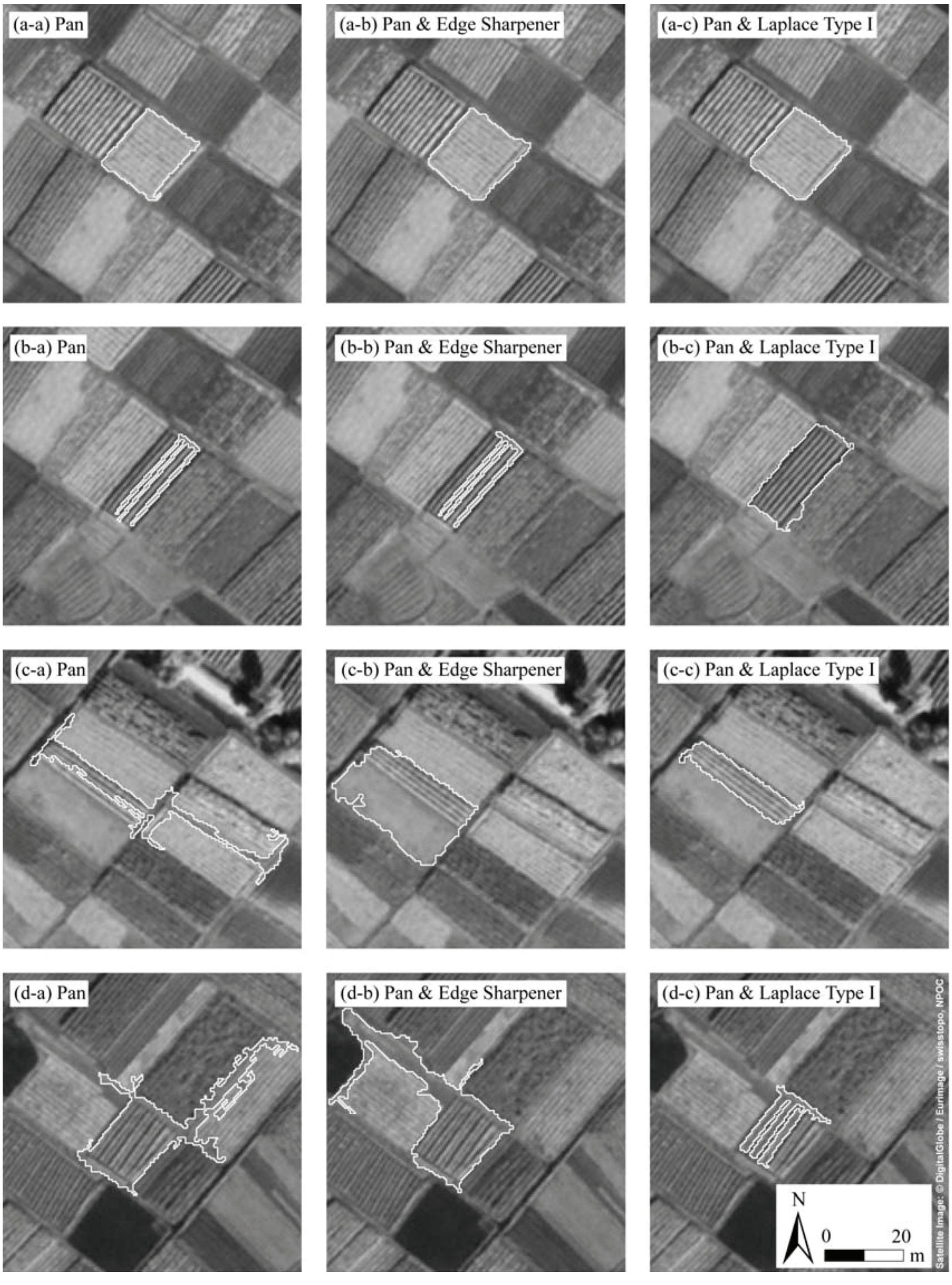


Figure 3. Field boundary delineation for selected fields based on the pan (column a), pan & edge sharpener (column b) and pan & Laplace Type I (column c) filtered bands.

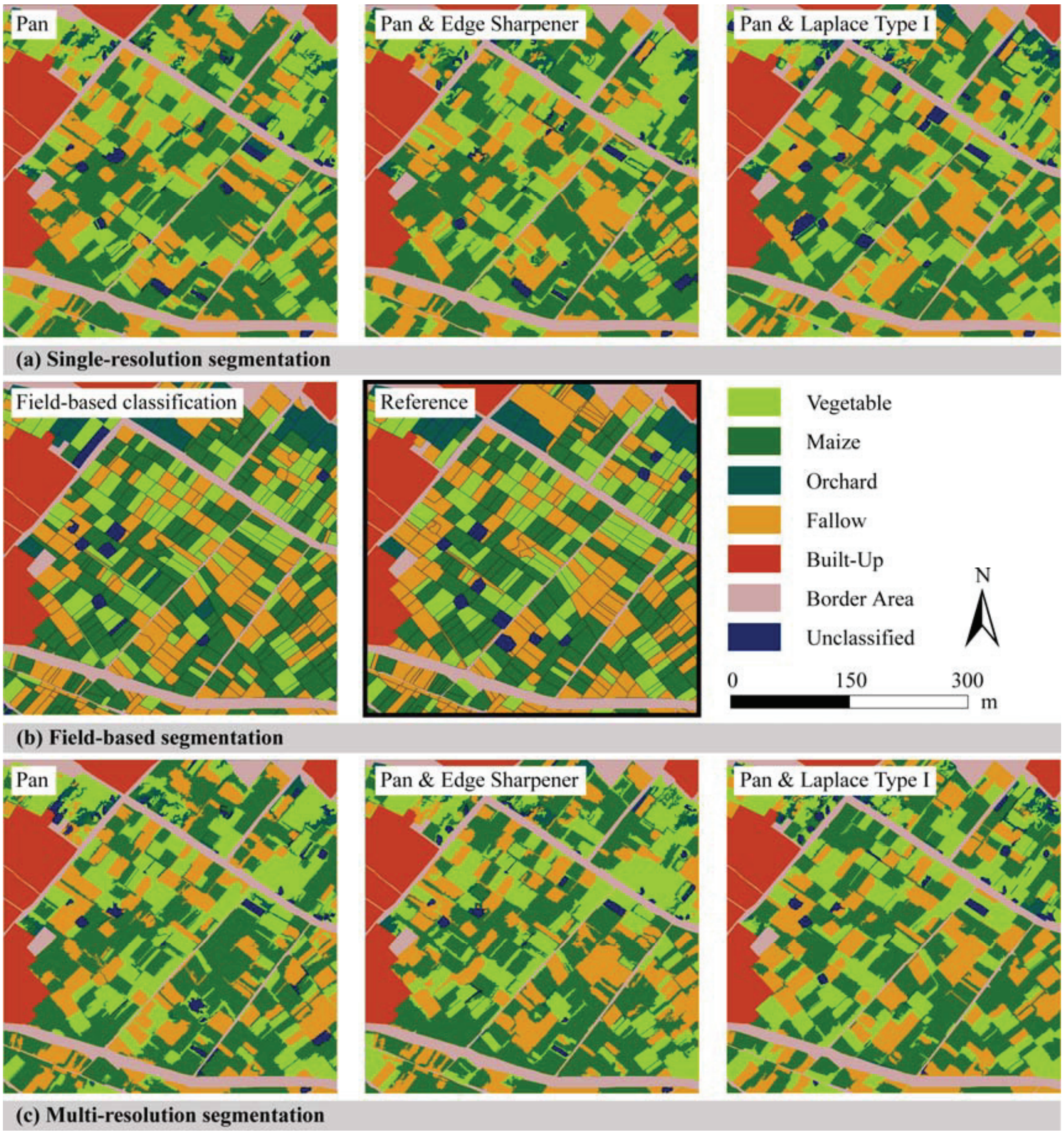


Figure 4. Comparison of single-resolution (a), multi-resolution (c) and field-based segmentation (b) and classification.

Comparison of the classification results with an error matrix underlined the impression of visual interpretation (Table 2). Average classification accuracy was slightly increased from single to multi-resolution segmentation. Overall accuracy was also somewhat higher in the case of multi-resolution segmentation. The kappa coefficient also performed slightly better. Inclusion of the edge sharpened and Laplace Type I filtered bands improved classification, but did not lead to substantial changes. Per-field vector segmentation and classification performed best in all approaches. The panchromatic band, the panchromatic & edge sharpened and the panchromatic & Laplace Type I filtered bands achieved an average accuracy of 51–56% for single-resolution segmentation and 51–54% for multi-resolution segmentation. However, the average accuracy of per-field vector segmentation scored almost 88%. Overall accuracy of per-field vector segmentation was similar; single and multi-resolution segmentation ranged between 56 and 60% for the panchromatic band, the panchromatic & edge sharpened and the panchromatic & Laplace Type I filtered bands, whereas the per-field vector segmentation scored 84%. The kappa coefficient (0.77) of the per-field vector segmentation was very good and far better than for the panchromatic band, the panchromatic & edge sharpened and the panchromatic & Laplace Type I filtered bands, whose kappa (0.37–0.42) scored into a fair to poor range (Monserud and Leemans, 1992).

Table 2. Classification-based field boundary accuracy assessment (error matrix) based on expert knowledge classification.

	Object-based segmentation & classification			Per-field segmentation & classification
	Pan	Pan & ES[a)]	Pan & Laplace[b)]	Vector
Average accuracy (%)[1)]	50.77	50.27	53.8	87.75
Overall accuracy (%)[1)]	56.42	56.17	60.01	83.99
Kappa coefficient[1)]	0.37	0.37	0.42	0.77
Average accuracy (%)[2)]	51.01	52.86	55.79	--
Overall accuracy (%)[2)]	57.54	58.67	59.23	--
Kappa coefficient[2)]	0.39	0.41	0.42	--

[1)] Single-resolution segmentation, [2)] Multi-resolution segmentation
[a)] ES: Edge Sharpener, [b)] Laplace: Laplace Type I

4.2 Communal level classification

The field boundary accuracy assessment in section 4.1 revealed that best classification was achieved for per-field vector segmentation. Hence, a per-field vector layer was created, segmented and labelled for all six villages in the commune, where over 95% LCLU coverage was reached (Figure 5). Visual inspection shows a high fraction of correctly classified vegetable, maize, orchard, and fallow fields. Orchard and fallow land was generally well identified. Classification of vegetable and maize, however, was recognized as more difficult.

The outcome of the quantitative accuracy assessment of the LCLU classification yielded similarly good results (Table 3). Producer accuracy was lowest for ‘vegetable’ (68%) and highest for ‘maize’ (92%). However, user accuracy was lowest for maize (66%) and highest for fallow (96%). The class kappa coefficient was lowest for ‘maize’ (0.57) and highest for ‘fallow’ (0.89).

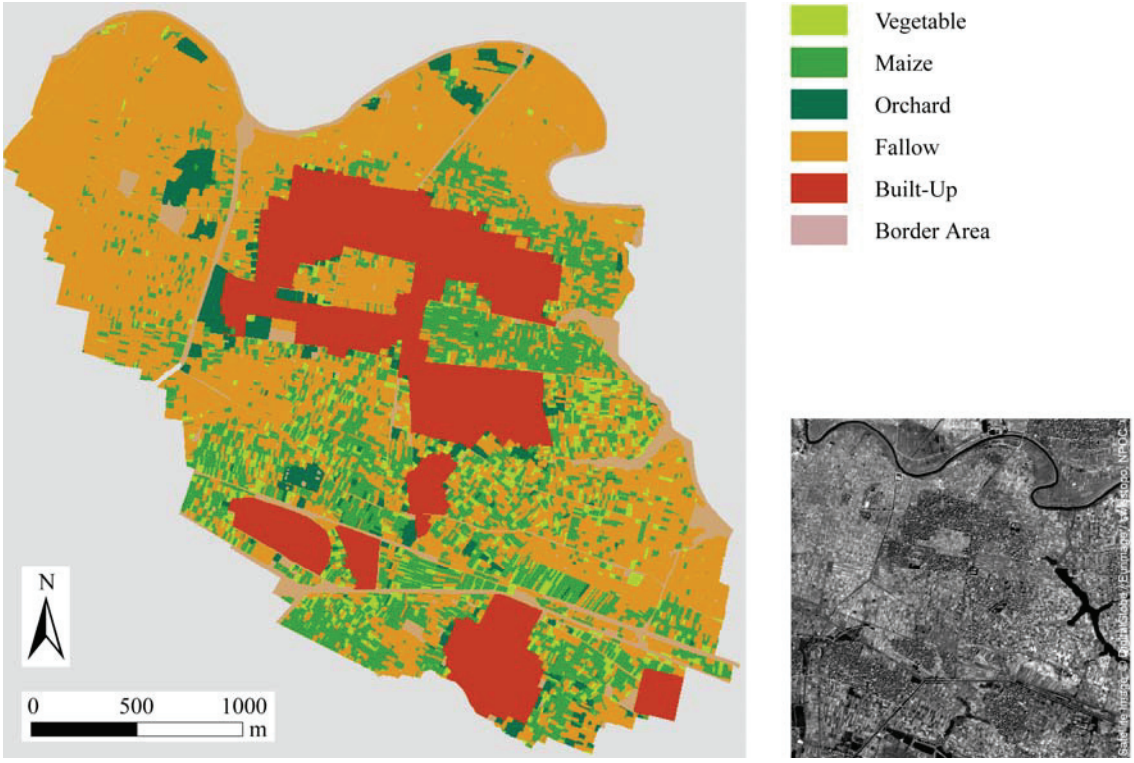


Figure 5. Per-field land cover/ land use classification of the commune Bac Hong, Dong Anh district, Vietnam.

About 19 of 60 test fields of the ‘vegetable’ class were erroneously identified as ‘maize’. Nevertheless, only 3 of 106 test fields of the ‘maize’ class were erroneously classified as ‘vegetable’, while six test fields as ‘fallow’. The class ‘vegetable’ accounts for many different crops (e.g. cabbage, kohlrabi, broccoli, peanuts, and cowpea). The diversity of crops in the ‘vegetable’ class, coupled with varying phenological stages, included a wide range of spectral, textural and morphological features. However, ‘maize’ was probably more easily identified due to its strong uprising leaves and closed canopy at the shooting stage. At maturity, however, it developed more bended and hanging leaves with a more open canopy. The maize texture changed with the phenological stage but its diversity was far less than that for ‘vegetable’. Orchard objects were also mislabelled and classified as ‘vegetable’ or ‘maize’. Though planted according to distinct patterns (e.g. line, chessboard), the newly planted orchards with small young trees may have a poorly formed canopy. Since the gaps gave room for sporadic weed growth or were used for maize and vegetable cropping, clear distinction and separation was difficult. In the most widely distributed 'fallow' class, 50 of 331 fields were erroneously classified. Sporadic growth of weeds may lead to a completely developed canopy with characteristics similar to those of young maize, thus explaining most of the misclassifications. A minor portion of erroneously labelled 'fallow' was classified as 'vegetable', mainly because of the wide range of values of the class 'vegetable'. An overall classification accuracy of 83% and a kappa coefficient of 0.7 can be considered a good to very good classification (Monserud and Leemans, 1992).

Table 3. Classification accuracy assessment based on field test samples at communal level.

	Vegetable	Maize	Orchard	Fallow
Producer accuracy (%)	68.33	91.51	80	85.2
User accuracy (%)	74.55	65.54	80	96.25
Class kappa coefficient	0.71	0.57	0.80	0.89
Overall accuracy (%)	83.11	Overall kappa coefficient		0.70

Class proportional sampling, test sample size n = 500.

5 Discussion

5.1 Field boundaries

Image segmentation is a crucial step in object-based LCLU classification. The results of this study revealed a good identification of apparently rather large homogeneous fields with considerable contrast in grey values to neighbouring fields. The filtered panchromatic bands (including the edge sharpener and Laplace Type I edge detector) further improved field boundary delineation. Yet, as most fields in this study are heterogeneous, a clear determination of fields and field boundary zones turned out to be difficult. Segmentation of the single panchromatic band was unpredictable and resulted in meaningless objects. Contextual information, such as field shape and cropping pattern, was hardly taken into account, and the algorithm failed to delineate field boundaries. Nevertheless, segmentation results were improved by additionally including the edge sharpened and Laplace Type I filtered bands. However, depending on the degree of within-field and between-field variation, either the edge sharpened or the Laplace Type I filtered band proved more appropriate. Considering the diversity of within-field and between-field variation of a larger observation area (e.g. commune), selection of the appropriate filtered band remains difficult. Future studies should thus also consider more advanced filtering techniques such as anisotropic non-linear diffusion filtering.

Standard labelling algorithms subsequent developed are negatively affected if a field with distinctive field boundaries is not properly delineated. A training object, consisting of field and border zone area, greatly differs in spectral properties compared to a field alone. Labelling algorithms developed on objects with absurd shapes or incompletely delineated field boundaries and narrow ranges of feature functions will be difficult to assign to other geographical regions and increase the number of erroneously classified objects. An assessment of classification-based field boundary accuracy clearly highlighted the latter observation. Though, most fields revealed distinctive field boundaries and common geometric shapes, such as rectangular or rhomboid, segmentation resulted in meaningless object shapes. The following assignment to standard classes led to only about 50% correctly assigned pixels compared to 83% for the per-field vector segmentation. Compared to single-resolution or multi-resolution region growing, the per-field vector segmentation approach performed far better in diversified, small-scale agricultural landscapes.

5.2 Communal level LCLU classification

The per-field vector segmentation and classification approach was highly successful. However, time-consuming digitisation of field boundaries is one of the main constraints of per-field vector segmentation. Digitising costs for the entire commune were high in terms of working hour. Since farmers frequently change management of their fields and reallocate field boundaries, continuous updating of per-field vector data will be required. According to De Wit and Clevers (2004), the need to update field boundaries due to changes in field management is far less work-intensive than creating an initial crop field database. While this may be true for fields in The Netherlands or Europe, it may not apply to a diversified, small-scale agricultural system such as the one investigated in peri-urban Hanoi. Farmers grow several crops on different plots in the same field. Instead of one/two cropping season per year in temperate climate zones, subtropical and tropical regions possibly allow continuous cropping throughout the year (e.g. three or even more cropping seasons are possible). Since farmers cultivate different crops on their fields, and the proportion of each crop per field may vary between seasons, updating of the per-field vector data may require considerable more efforts in such an environment. Therefore, a segmentation technique capable of delineating distinct geometric shapes on small fields would greatly help periodic monitoring of LCLU in agriculture.

5.3 Additional LCLU classification aspects of diversified, small-scale agriculture

Owing to the agricultural diversity, multi-temporal image analysis for the entire year could possibly better address LCLU than analysis of a single image. Though spatial data from consecutive seasons (e.g. spring, summer and autumn) could enhance information on seasonal cropping patterns, the slot for acquiring a multi-temporal image dataset is limited to specific periods of time representing most of the agricultural diversity. De Wit and Clevers (2004) reported that two to three satellite images are required for agricultural LCLU classification in The Netherlands. Nevertheless, number and timing of satellite images are critical factors (Delecolle et al., 1992; Dorigo et al., 2007; Launay and Guerif, 2005). Assuming that LCLU classification in peri-urban Hanoi requires one image in spring and summer and two images in autumn, at least four images with specific time slots would thus be needed. Due to unpredictable weather forecasts, especially in tropical and sub-tropical regions and difficulty in acquiring high spatial resolution satellite images of the same geographic region within a year, alternatives such as airborne digital sensor (ADS) data in combination with Light Detection and Ranging (LiDAR) data should be considered. The aircraft mounted with ADS and LiDAR offers more flexibility in data collection and increases the chance of obtaining images that correspond better to the required time slots during the cropping seasons.

However, ADS and LiDAR data has further advantages over satellite images. The spatial resolution of the latest ADS sensors is far higher than that of commercial satellite images. The higher spatial resolution of ADS delivering multi-spectral bands of the same spatial resolution as the panchromatic band, combined with digital elevation and surface models derived from airborne laser data, is reported to substantially improve delineation of field boundaries (Buehler et al., 2007). Using high spatial resolution ADS and airborne laser data will likely expand the number of LCLU classes, but may not completely avoid the mixed pixel problem at field boundaries. The present study focussed on four specific LCLU classes only. Two of these classes (i.e. vegetables and orchard) comprise many subclasses relevant to be identified for agricultural purpose. Besides, airborne laser could also provide information on soil properties and cultivation systems (Davenport et al., 2003) and allow assessment of crop biomass (Hollaus et al., 2006; Hyyppa et al., 2008; Saeys et al., 2009; Walter, 2004).

6 Conclusion

Internal variability of high spatial resolution data increases with peri-urban agricultural diversity and is a challenge for LCLU classification. For detailed LCLU mapping, parcel-boundary extraction is favoured as it facilitates management and monitoring of complex landscapes. However, tests on the panchromatic band of Quickbird satellite image data and multi-resolution region growing algorithms revealed that parcel boundaries cannot be sufficiently extracted. Additional pre-processing (i.e. high-pass filters) hardly improved field boundary delineation and thus classification accuracy. A comparison of object-based and per-field agricultural LCLU classification methods indicated that the per-field classification method was far more adapted to this diversified, small-scale agriculture pattern. Consequently, a per-field vector layer was created, segmented and labelled/classified. Classification results were very promising thanks to their overall accuracy of 83% and kappa coefficient of 0.7 using pan, filtered pan, NDVI, green and blue band values, as well as band variables. Though the per-field vector segmentation and classification approach was superior for LCLU classification of diversified, small-scale agriculture, it also revealed disadvantages. Preparation of per-field vector data is highly time-consuming, largely based on expert knowledge and requires frequent updating if used for multi-temporal analysis and monitoring of such diverse environments.

Successful field boundary delineation algorithms could significantly improve object-based classification. In order to further enhance accuracy of field boundaries delineation, use of high spatial resolution multi-spectral data from ADS is suggested. The ADS data also allows improved use of spectral and textural features, likely to increase separability of classes and number of LCLU classes under investigation. In combination with LiDAR data, soil properties and crop biomass could be derived and used as additional field parameters for classification of crops in diversified landscapes.

Chapter 5

Upscaling nutrient flows to communal level – Outline of a methodology

1 Introduction

To draw the attention of policy-makers and urban planners to recycling and reuse aspects, different methods and tools have been developed and waste management scenarios investigated. Life cycle assessment (LCA) models are, for instance, tools to assess the environmental impact of a product from cradle to grave (Binder et al., 2003). They can be used to calculate waste flows, resource consumption and environmental emissions from waste management systems. They further allow impact assessment in terms of potential global warming, acidification or nutrient enrichment (Kirkeby et al., 2006). Material flow analysis (MFA) is another well-known method applied. This method can be used for systematic assessment of flows and stocks of material within a system defined in space and time. The results of MFA can be verified by a simple material balance of all inputs, stocks and outputs of a process (Baccini and Bader, 1996; Brunner and Rechberger, 2004). MFA can be applied to developing countries, as it allows resource flow analysis of a small town or an entire city. It can evaluate especially the impact of changes in consumption, solid waste and wastewater treatment infrastructure, peri-urban agricultural production, including waste and wastewater reuse practices on resource use and environmental pollution (Montangero et al., 2007). MFA has been successfully applied in developing countries and reported as a useful tool for waste management (Belevi, 2000; Gumbo et al., 2003; Montagero et al., 2004; Montangero et al., 2007).

These tools provide a good overview of the flows in a city or town; however, they often neglect the important spatial component. As regards management of waste flows, the spatial component is crucial, as economic scenarios are calculated as a function of geographic determinants. For instance, if organic waste from an inner-urban ward is to be recycled and reused in peri-urban agriculture, economic feasibility will largely dependent on transport distance from the waste generation source to its reuse point. Therefore, the closest peri-urban agricultural commune will not necessarily be capable of reusing all the organic waste generated by the inner-urban ward. The agricultural landscapes can be highly diverse and vary over space and time. Applied to urban and peri-urban agriculture, production systems may change from one commune to another. While some communes are strong in vegetable production, others just grow staple food crops. Consequently, crop nutrient requirements also change according to the production system in place, and thus also influence the reuse potential of organic waste. Tools for organic waste management should thus also include the agricultural production system and assess spatial and temporal variations.

Agricultural research responded to the increased need for spatial nutrient management planning tools. For instance Kang et al. (2007) recently reported on a comprehensive GIS system in providing improved waste management strategies in terms of optimal land application and transport analysis for sustainable on and off-farm poultry litter utilisation. Also Paudel et al. (2009) presented a GIS model with incorporated land use types, location of dairy farms and farm land, as well as road networks allowing to assess dairy manure transport routes with a view to minimise costs relating to environmental constraints. Though incorporation of the spatial component is highly acknowledged, these tools have mainly been developed for large-scale farm management systems in North America and may be difficult to apply to urban and peri-urban production systems. Furthermore, they seem to neglect analysis of the prevailing production system (i.e. type of crop and applied amount of organic and inorganic fertiliser nutrients).

However, when developing waste management scenarios, particular attention should be paid to the agricultural system in place, with special emphasis on nutrient flows, to avoid surplus application of fertilisers leading to environmental pollution. The objective of this chapter is to explore and describe the feasibility of upscaling nutrient flows from field to village and communal level as a function of the diverse, small-scale agricultural production systems in the peri-urban area of Hanoi, Vietnam. The work intends to highlight the importance of spatially and temporally explicit nutrient flows to be considered when developing organic waste reuse scenarios.

The outline of the methodology is based on results and experiences from previous work presented in chapters 2 to 4. The following section 3 presents analytical steps for peri-urban agricultural environmental analysis. Section 4 describes the modelling of crop rotations, while section 5 presents the modelling of nutrient flows. In section 6, development of waste reuse scenarios is discussed, and section 7 presents an overall view and a brief outlook of the methodology.

2 Analytical steps

Where spatial and temporal patterns in urban and peri-urban cropping systems are unknown, the presented analytical method may provide a guideline for determining these patterns. The method has been successfully implemented at village and communal level and can be recommended for analysis in comparable environments. The method makes use of three main components: (a) farming system survey, (b) GIS and (c) remote sensing (RS) (Fig. 1). Four different analytical steps are identified in the process of investigating the spatial and temporal patterns of urban and peri-urban cropping systems: (i) analysis of land use I, (ii) analysis of crop rotations, (iii) analysis of nutrient flows, and (iv) analysis of land use II.

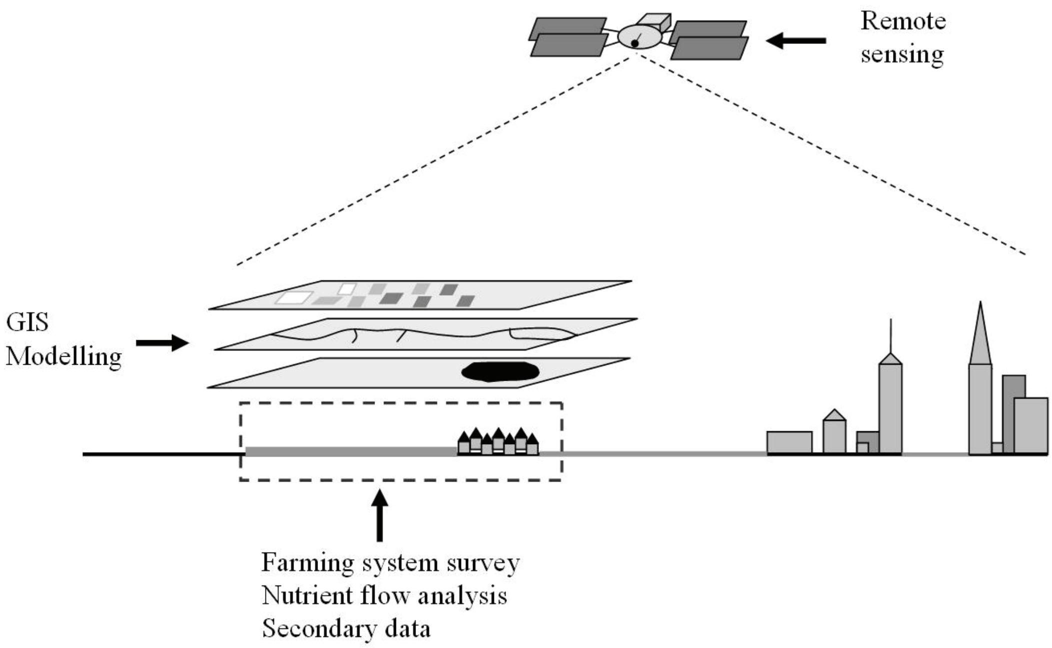


Figure 1. Overview of the methods used to analyse the patterns in cropping systems.

2.1 Analysis of land use I

The objective of this step is to obtain a first broad picture of the farming systems in place with special focus on land use. It can be seen as a qualitative analysis consisting of map surveys, collection of statistical data, expert interviews, farmer group discussions, and transect walks. Though maps are often scarce or outdated, they provide a first overview of the geographic situation. They can be of different origin and scale. Land use, land register and soil maps are of high interest, but also geographic maps with road infrastructure are useful. Statistical data will inform about the cropping area and main crops cultivated. Also livestock numbers can be retrieved from statistical data. Where statistical data is not available, expert interviews may help to improve our understanding of the farming system in place and provide general information on the cropping and livestock systems. Expert knowledge on the agricultural system in the commune is also used to draw up lists of farmers who are invited to farmer group discussions. The selected farmers should be representative of their commune and cultivate fields in different parts of the village. The farmer group discussions are used for participatory mapping of land use/land characteristics at village level. The village land is divided into sectors to allow a spatial stratification. Farmers will then identify their fields in the different sectors, select major crops for the respective cropping season and classify soil fertility and water availability. In an additional exercise conducted on exemplary farms with given fields at different distance intervals, farmers debate on crop rotations and on organic and inorganic fertiliser application depending on cropping season. Finally, the farmers join the transect walk through the village. The transect walk is dictated by topography, soil fertility levels and spatial cropping patterns.

2.2. Analysis of crop rotations and associated nutrient flows

The second step aims at exploring possible spatial and temporal patterns in the cropping systems and corresponding nutrient flows. It involves a rather quantitative analysis consisting in farm sampling, farm survey, data pre-processing, and statistical analysis. A stratified sampling of farmers' fields is essential to achieve plausible results. The village map of the farmer group discussions described in the previous section 'Analysis of land use I' includes stratified fields. These should be selected in such a way as to represent all sectors, and the crops of the selected fields should correspond to the major crops used in the sector. The actual farm survey mainly focuses on cropping patterns and associated nutrient flows. The team visits all the fields together with the farmers and discusses the site characteristics of each field (e.g. soil fertility level, water availability and relative elevation topography), the cultivated crops, and management of organic and inorganic fertilisers. Each annual cropping season is recorded separately. A differential GPS is used to spatially locate the field and measure field and plot area. The latter is an important parameter to verify the actual amounts of fertiliser applied, especially where inorganic fertilisers are frequently used. In addition to crop data, information on farm livestock number is also recorded.

Data pre-processing includes field data collection in an advanced database (e.g. MSAccess®, MySQL®), computation of crop rotations and compilation of field characteristics. Diversity of urban and peri-urban agriculture will lead to numerous crop rotations. For purposes of statistical analysis and combination with remote sensing data, the number of crop rotations has to be reduced and simplified. For instance, a classification according to staple and cash crops may lead to the necessary reduction in crop combinations. Data pre-processing is then used to aggregate nutrient flows and calculate partial nutrient budgets. Full nutrient budges are desirable, however, they include variables that are largely unknown, such as atmospheric deposition, sedimentation or subsoil exploitation. Since variability in cropping systems of urban and peri-urban agriculture is high, partial budgets seem more appropriate. Nutrient flows and budgets should not only be calculated for each crop and cropping season, but also at field level for the entire crop rotation over different cropping seasons. Calculation of nutrient flows and budgets for the entire crop rotation takes stockpile application or soil nutrient mining better into account (i.e. nutrient surplus or deficit). For instance, in the cropping season with little rainfall, farmers may apply large amounts of manure to facilitate transport of the bulky material to the field. The monsoon growing seasons may, however, receive less organic fertilisers. Thus, separate analysis of the cropping seasons or the entire crop rotations may provide an entirely different picture.

Statistical analysis can be divided into analysis of crop rotations and analysis of nutrient flows. Farmer's choice and management of crop rotations is assumed to be governed by environmental and socio-economic factors. Presence or absence of crop rotations requires, for instance, analysis of the influencing factors. Analysis of crop rotations is thus based on logistic regression, a statistical technique to analyse probability of a categorical dichotomous outcome explained by a set of independent, continuous or categorical variables (Forster et al., 2009a). Important informative variables to be tested comprise distance from village to field (e.g. built-up buffer distance), distance from road to field (e.g. road buffer distance), plot size, perceived soil fertility, water availability, relative elevation topography, and livestock number. One or several of these variables are likely to explain the presence or absence of tested crop rotations. Maximum likelihood estimates, standard error (S.E.), Wald statistic (χ^2), and the odds ratio are then used to verify model performance. To further compare the overall performance, ROC (Receiver Operation Characteristics) and AUC (Area Under Curve) are calculated.

Statistical analysis of nutrient flows is closely related to crop rotations (Forster et al., 2009b). Analysis of variance (ANOVA) and corresponding post-hoc procedures are applied to determine differences in nutrient flows. Non-normally distributed data and heterogeneity of variance may require the use of non-parametric tests. Analysis of covariance (ANCOVA) is used to assess the covariates influencing the dependent variable. Again, rank transformed ANCOVA may be preferred where data is non-normally distributed or heterogeneity in variance is observed. The same covariates as for analysis of crop rotations may be used (e.g. built-up buffer distance, road buffer distance, plot size, perceived soil fertility, water availability, relative elevation topography, and livestock number).

2.3 Analysis of land use II

The objective of this step is to quantitatively assess land cover/land use by remote sensing (RS) and GIS. Thus, land use (i.e. crop types or groups of crops) is identified on the basis of space or airborne sensor data (Forster et al., 2009c; Forster et al., 2009d). The procedure comprises image data selection, image data pre-processing, digitisation of field boundaries, development of labelling algorithms, land cover/land use classification, and accuracy assessment. As urban and peri-urban agriculture is highly diverse and small-scaled, high spatial resolution image data is required to capture the details of the cropping systems. Spaceborne sensors, such as Quickbird, Ikonos or Spot 5 HRG, provide very high spatial resolution data with submeter resolution for the panchromatic, and 2–4 m spatial resolution for the multi-spectral bands. Conversely, airborne digital sensors (ADS), such as ADS40, allow ground sampling distances down to 5 cm for panchromatic, multispectral and infrared bands. The latter data is more suitable for analysis of urban and peri-urban land cover/land use, however, it is not yet widely available, especially not in developing countries. Spaceborne sensor data may thus be used for land cover/land use analysis.

Data pre-processing includes resampling, radiometric and geometric correction, as well as image registration (i.e. geo-referencing). Conventional GIS software is applied to digitise field boundaries and to create a polygon per-field vector layer. Panchromatic and multi-spectral bands are then used in an object-based fuzzy classification approach. A segmentation based on the polygon per-field vector layer creates objects or segments of the fields surveyed. Training areas, representative of land cover/land use in the commune, serve as a basis for developing the labelling algorithm. A multitude of membership functions can be applied to classify image objects into categories at specific segmentation levels. Potential membership functions are based on spectral, textural, morphological, and topological features. Spectral features make use of the spectral properties of a field in order to label it to a specific land cover/land use category. Textural features analyse the variation of grey level values of adjacent pixels and their specific spatial distribution. At field object level, the textural feature allows to characterise within-field variation resulting from different cultivation strategies. Morphological features address the shape of an object (e.g. length/width), whereas topological features relate the position of an object to another in the spatial context (e.g. relative border to). Features such as NDVI or primary and secondary features of filtered bands (i.e. Sobel Edge Detector and Laplace Types I) may also provide a good basis for decision-making. Once the labelling algorithm is developed, large areas are rather quickly classified. Finally, classification accuracy is assessed by an error matrix, which compares objects of discriminated classes to objects in the reference data. Indices, such as overall, producer, user accuracy, and Kappa coefficient, are calculated.

After implementation of the steps described, the investigator will have acquired a sound understanding of the cropping system in place. One or several crop rotation models are developed, the corresponding nutrient flows are analysed and land cover/land use is assessed based on very high spatial resolution image data. The obtained data may now be further used in modelling the nutrient flows at village or communal level.

3 Modelling crop rotations at village or communal level

Modelling of crop rotations is strongly dependent on the variables explaining the likely occurrence of crop rotations. Thus, the data required may differ from one region to another. Data from an earlier study was used in this work. The study investigated crop rotations for their spatial explicitness and suitability to predict land use over time (Forster et al., 2009a). Rice paddy dominated the first and second cropping season, followed by crop rotations with vegetables, maize and sweet potato. To reduce the number of possible combinations in crop rotations, agricultural land use was recoded into fallow land, staple and cash crops. Vegetables, maize and sweet potato were considered as cash crops (C), rice was labelled as staple crop (S) and fallow land was termed as F. The results obtained by logistic regression revealed that distance to the field was a major informative variable. However, also perceived soil fertility greatly influenced occurrence of crop rotations. The likelihood of finding cash crop-dominated rotations (CCC) was highest on close fields with perceived high soil fertility. With additional distance and lower soil fertility, cash crop-accentuated (SSC) rotations were likely to increase. Finally, the likelihood of finding SSF was highest on remote fields. Consequently, a separate model for each crop rotation was developed to allow prediction of the rotation as a function of major variables such as distance and perceive soil fertility.

Modelling of crop rotations will thus require information on distance and soil fertility. Distance intervals (i.e. built-up buffer) can be created by the multiple buffer function in GIS. Soil fertility can be retrieved from farmers' participatory soil fertility mapping or from a detailed soil fertility map. Data is then transformed into GIS-raster layers (Fig. 2). Based on the statistical model developed under 'Analysis of crop rotations and associated nutrient flows', the likelihood of a specific crop rotation to occur is predicted and transcribed into each grid cell. The grid cell exhibiting the highest likelihood then determines the type of crop rotation.

Lookup table for map values and predicted likelihood (LH) of crop rotations

Distance	Soil fertility	LH SSF	LH SSC	LH CCC	Crop rotation
1	3	0	0.3	0.7	CCC
1	3	0	0.3	0.7	CCC
1	2	0.1	0.5	0.6	CCC
2	2	0.1	0.6	0.3	SSC
2	1	0.4	0.5	0.1	SSC
3	1	0.8	0.2	0	SSF
3	1	0.8	0.2	0	SSF
3	1	0.8	0.2	0	SSF

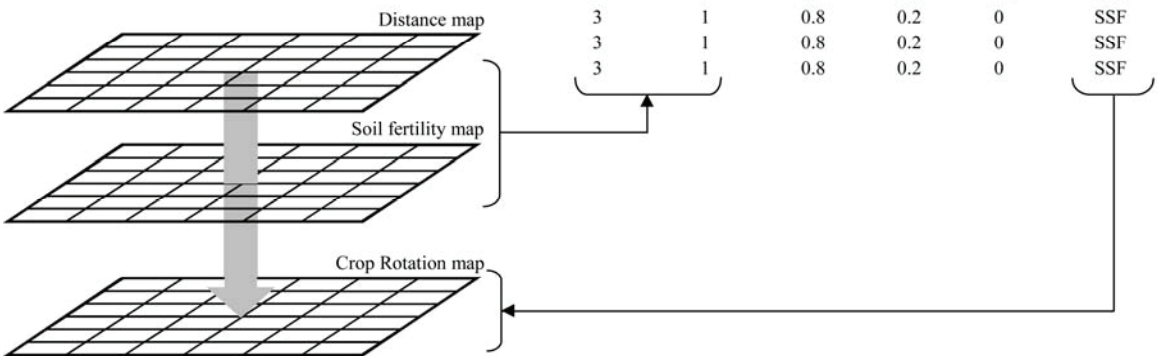


Figure 2. Example of modelling spatially explicit crop rotations as a function of distance and soil fertility.

Where no soil fertility map is available or where the degree of detail is insufficient, modelling of crop rotations may be based on distance and remote sensor land cover/land use data (Fig. 3). In a first step, distance intervals are used to predict the likelihood for a specific crop rotation to occur. The highest likelihood again determines the rotation. Remote sensor land cover/land use data is then used to adapt the crop rotation to the actual land use in place. If the model predicted a cash crop (C) and land cover/land use assessment fallow land (F), the rotation with F in the last season of the year is selected as the consolidated crop rotation (Fig. 3*). Conversely, where model and land cover/land use assessment both indicate a cash crop for the last season in the year, the model with the higher likelihood determines the consolidated crop rotation (Fig. 3**). This is because there are two distinct crop rotations (i.e. SSC and CCC) with cash crop during the third season, but different spatial distributions.

Lookup table for map values and predicted likelihood (LH) of crop rotations

Distance	LH SSF	LH SSC	LH CCC	Crop rotation	Land cover/ land use	Consolidated crop rotation
1	0	0.3	0.7	CCC	- - C	CCC**
1	0	0.3	0.7	CCC	- - C	CCC**
1	0.1	0.5	0.6	CCC	- - F	SSF*
2	0.1	0.6	0.3	SSC	- - C	SSC**
2	0.4	0.5	0.1	SSC	- - F	SSF*
3	0.8	0.2	0	SSF	- - F	SSF
3	0.8	0.2	0	SSF	- - F	SSF
3	0.8	0.2	0	SSF	- - F	SSF

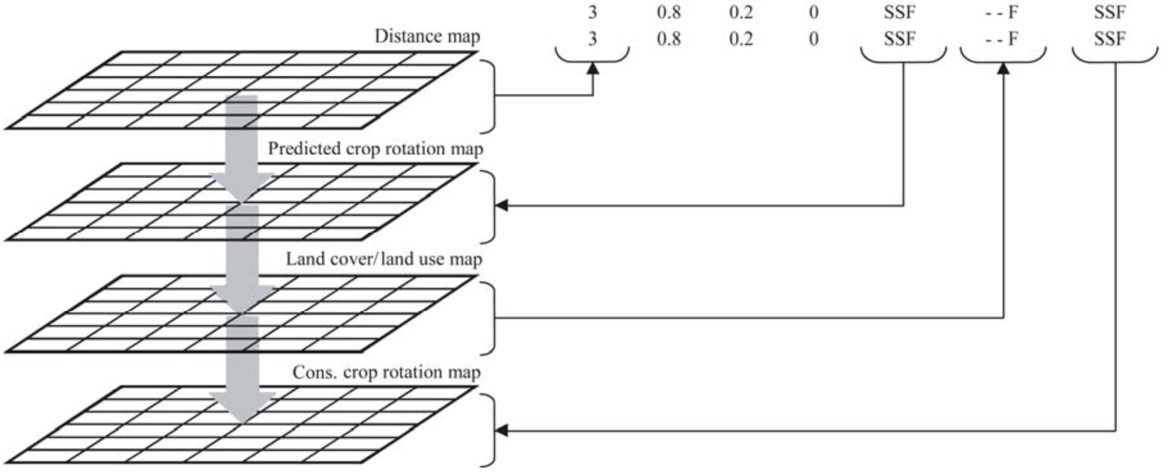
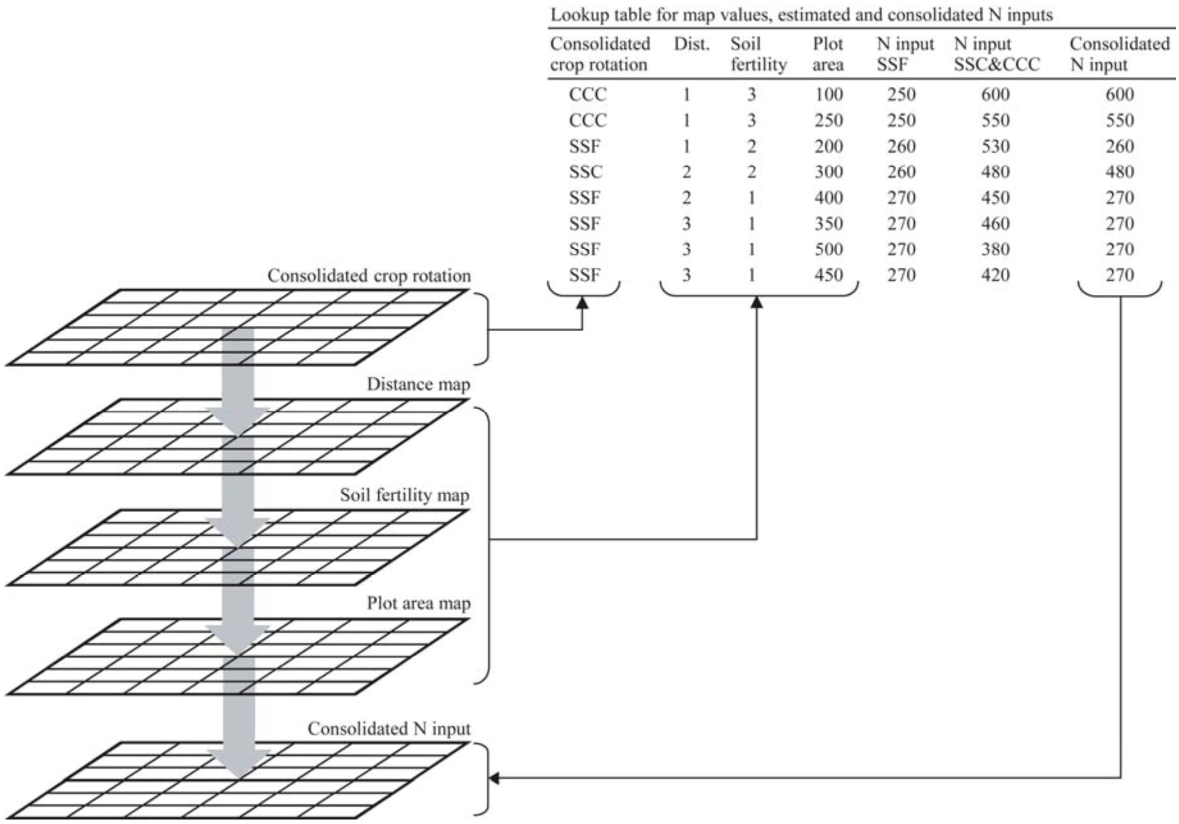


Figure 3. Example of modelling spatially explicit crop rotations as a function of distance and remote sensor land cover/land use data.

4 Modelling of nutrient flows at village or communal level

Modelling of nutrient flows depends primarily on the consolidated crop rotation. However, nutrient flows may also be influenced by site characteristics. This section of the work refers to an earlier study exploring nutrient flows linked to spatially explicit crop rotations (Forster et al., 2009b). Nitrogen fertiliser inputs were used as indicators for nutrient flows to staple crop-based (SSF), cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. SSC & CCC achieved average organic, inorganic and total nitrogen fertiliser inputs of 112, 384 and 496 kg ha^{-1}, respectively. Conversely, SSF rotation achieved average organic, inorganic and total nitrogen fertiliser inputs of 52, 209 and 261 kg ha^{-1}, respectively. Thus, average organic, inorganic and total nitrogen fertiliser inputs for SSC & CCC rotation were significantly higher than those for SSF. Also total nitrogen fertiliser input for CCC (543 kg ha^{-1}) was significantly higher than for SSC (475 kg ha^{-1}). Furthermore, rank transformed ANCOVA proved that built-up buffer distance, plot size and soil fertility explained much of the variation.

Modelling of nutrient flows is determined by the respective crop rotation and by the corresponding models developed in section 3.2 'Analysis of crop rotations and associated nutrient flows'. In this case, the variables of built-up buffer distance, soil fertility and plot size play a key role in the prediction of flows and are transformed into GIS-raster layers (Fig. 4). Where soil fertility maps are unavailable, soil fertility indicators could be retrieved from participatory soil fertility maps or remote sensing data. In the latter case, soil fertility can be deduced from analysis of land cover/land use of high spatial resolution data or, according to Omuto and Shrestha (2007), by multi-temporal analysis of Landsat ETM^+ data. The model then predicts input flows based on the given variables. Input flows that correspond to the consolidated crop rotation are then selected. The lookup table in Figure 4 presents an exemplary case of nutrient flows. In general, total nitrogen fertiliser inputs for SSC & CCC rotation increase the closer the fields to the village, the less the perceived soil fertility and the smaller the fields. The same applies to the SSC rotation but at a lower input level. However, for SSF crop rotation, total nitrogen input is not affected by distance or plot area, but only by soil fertility. This procedure can be repeated with models predicting inorganic or organic nitrogen fertiliser inputs. Also output flows can be linked to crop rotation and followed by computation of spatially explicit nutrient budgets. As an alternative to the output flow analysis, inputs to crop rotations may be compared to fertiliser recommendations. Finally, the spatial-temporal data on nutrient flows allows to develop waste reuse scenarios.



Consolidated crop rotation	Dist.	Soil fertility	Plot area	N input SSF	N input SSC&CCC	Consolidated N input
CCC	1	3	100	250	600	600
CCC	1	3	250	250	550	550
SSF	1	2	200	260	530	260
SSC	2	2	300	260	480	480
SSF	2	1	400	270	450	270
SSF	3	1	350	270	460	270
SSF	3	1	500	270	380	270
SSF	3	1	450	270	420	270

Figure 4. Example of modelling nutrient flows as a function of crop rotation, distance, soil fertility, and plot area.

5 Developing organic waste reuse scenarios at village and communal level

Knowledge of spatial-temporal nutrient flows is a basic requirement to develop organic waste reuse scenarios at village and communal level. Such scenarios may include organic and inorganic fertilisers used by the farmer. In this case, the objective is to assess the amount of nutrients that can be supplied to the commune by taking into account the amount already applied by the farmer. However, in the urban vicinity, availability and access to inorganic fertilisers are generally good and surplus applications frequent. Thus, the objective of the scenarios may rather tend to a potential organic waste reuse, provided inorganic fertilisers can and will be replaced. Organic waste reuse scenarios are developed in a GIS system, allowing integration of data on spatially explicit crop rotations and associated nutrient flows.

So far, only the nutrient aspects were considered in the development of waste reuse scenarios. However, aspects of waste quality should also be included. Quality of organic waste (solid or liquid) can vary considerably from fresh untreated faecal sludge with high nutrient and pathogen levels to well-treated and composted market waste with rather low pathogen levels. Application of fresh untreated faecal sludge on all communal land puts the vegetable cropping area at risk. Conversely, not all crops in the commune depend on well-treated compost as required by vegetables. Spatially explicit crop rotations and remote sensing data can provide information on spatial and temporal cropping patterns and specific requirements. This information can be included in the development of reuse scenarios with regard to different types of waste and their quality level.

Information on spatially explicit crop rotations and associated nutrient flows can also be used as a planning tool for decentralised waste treatment. Decentralised waste treatment plants are considered an alternative to conventional centralised sanitation systems. Thereby, households, neighbourhoods, villages or communes are responsible for appropriate waste treatment and disposal. Villages or communes lacking the capacity of providing treatment and disposal services may contract other villages or communes to carry out these services. Knowledge of cropping patterns and nutrient flows can now provide a useful basis for planning. For instance, where liquid waste (e.g. faecal sludge and wastewater) can be applied to crops, planning may consider the construction of a liquid waste treatment plant. Where vegetables are cultivated, construction of a composting plant for solid waste treatment may be more appropriate. Since spatial assessment of nutrient flows can also profit from optimised waste transport logistics, transport costs may be kept low.

6 Overall discussion and outlook

General consensus prevails among researchers regarding the underlying spatial and temporal variations in nutrient flows and their importance in nutrient budget estimations (Craswell and Lefroy, 2001; Schlecht and Hiernaux, 2004; Scoones and Toulmin, 1998). Furthermore, the hierarchy of scales is not the same for all processes involved. For instance, village and commune borders generally do not match the borders of catchments and watersheds. Geographical information systems (GIS) in combination with modelling of nutrient flows is recommended to bridge existing gaps in nutrient budgets and balances at different spatial scales (Schlecht and Hiernaux, 2004). The analytical steps suggested in the preceding sections respond to the latter request and include modelling of communal land use and its incorporation into GIS. Furthermore, integration of remote sensor data – allowing for site-specific assessment of land use – is suggested to reduce uncertainty regarding spatial cropping patterns. Successful development of models based on crop rotations also offers the possibility of land use prediction over time. Nutrient flows linked to crop rotations provide spatial and temporal data for environmental monitoring. Their implementation at village and communal level allows land use and management issues to be addressed directly by the responsible administrative unit.

The question on the possible number of crop rotations included in the models remains an interesting topic requiring further research. As experienced when implementing step 'Analysis of crop rotations and associated nutrient flows', it was difficult to subdivide cash crops into maize and vegetables. A subdivision would have increased the number of possible crop combinations from three to twelve, but would have required a much larger sample size to achieve plausible results. However, from the viewpoint of land cover/land use analysis based on remote sensor data, it was possible to separate maize from vegetables. Validation of seasonal (temporal), spatial cropping patterns by remote sensor data is highly justified. Yet, the approach would require data over specific time periods covering consecutive cropping seasons. High spatial resolution satellite data is also prone to foul weather, especially in the tropics and subtropics, and to higher priority orders of satellite image agencies. A more flexible use and increased spatial resolution can be achieved with the aircraft-mounted ADS sensors. As operation height is adjustable, the aircraft is also capable of undertaking flight missions under cloudy conditions. ADS would allow identification of different groups of vegetables. In combination with airborne laser data (ALD), additional information on soil properties and cultivation systems (Davenport et al., 2003) may be retrieved and crop biomass estimated (Hollaus et al., 2006; Hyyppa et al., 2008; Saeys et al., 2009; Walter, 2004).

Models based on spatially explicit crop rotations and associated nutrient flows naturally raise the question of transferability of the methodology to other communes of the same region or to communes of different regions. The question cannot be fully answered at the time, as the approach was not applied to other communes. However, the following reflections may provide a clue of the potential future challenges. Production factors, such as climate, soil, water, topography, and exposition, form the basis for any decision. Appraisal of production factors by the farmer and the social rules prevailing in the community may guide the farmer's decision and, thus, influence the composition of crop rotations. The cultivated crops and available and accessible organic or inorganic fertilisers will lead to varying nutrient flows. For instance, where available per capita land is high and soil fertility low, the staple crop-based rotations may be more pronounced than other rotations. Conversely, high soil fertility and low per capita land availability may lead to more cash crop-influenced rotations, and thus differ from staple crop-based rotations in terms of nutrient flows. Consequently not only production conditions may vary from one village to another, but also crop rotations and associated nutrient flows. If the methodology is to be applied to another region, the crop rotation and nutrient flow models will have to be validated. However, if the models are applied to neighbouring communes, land cover/land use derived from very high spatial resolution image data may partly offset the differences in spatial cropping patterns.

Improved understanding of a farming system offers the opportunity to include scenarios induced by changes in model parameters. A possible scenario could include decreasing soil fertility over a long-term period or it could pursue a concentration of cash crops such as vegetables. Conversely, distinct preferential applications of organic fertilisers close to the village could also be simulated or the increased use of organic fertiliser due to growing livestock number. However, the methodology may not only contribute to developing scenarios for agro-ecosystems, but may also provide an approach for effective reuse of organic waste in urban and peri-urban agricultural production systems.

In the peri-urban commune of Bac Hong, Hanoi, for example, organic manure is still highly appreciated by farmers. In general, total nitrogen fertilisers supplies are sufficient to meet the crops' nutrient requirement. However, since organic fertilisers cover only a small fraction of the crops' total nitrogen requirement (20 – 30%), reuse of organic waste still has an important development potential. Surplus application of organic fertilisers has not been observed, however, surplus application of inorganic fertilisers may, in some cases, give cause for concern. Additional organic waste reuse in the commune could contribute to reducing application of mineral fertilisers. As mentioned earlier, possible obstacles include costs associated with transport of the organic waste, its quality (e.g. pathogens, heavy metals etc.), as well as farmer incentives for using the rather bulky organic waste instead of easily manageable mineral fertilisers.

Spatial and temporal assessment of the organic waste reuse potential would allow decentralised waste treatment facilities to be planned as close as possible to the reuse areas. In the Bac Hong commune, cash crops, such as maize and vegetables, are grown close to the built-up area. Concerning reuse of sanitised waste in vegetable cultivation, composting plants should be constructed close to the vegetable area. Reengineering peri-urban agricultural production systems towards organic waste reuse should also be considered. This could include the introduction of new crops allowing the reuse of low quality organic waste through existing irrigation systems. Or it could implicate a strong focus on vegetable production where good quality composts can be used. Thus, urban and peri-urban agriculture could wilfully become an integrated component of urban planning with the mandate to reuse the urban organic waste and supply food to the increasing urban population. However, policy interventions are urgently needed to reintroduce the urban-peri-urban linkage, increase nutrient use efficiency and foster organic waste reuse in urban and peri-urban agricultural production systems.

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Appendices

Appendix 1: Spatially explicit land cover/land use models based on remote sensor data

If spatially explicit crop rotation models can be developed based on farm survey data, it should be feasible to draw statistical models from remote sensor data on land cover/land use (LCLU). To prove this assumption, classified LCLU of the Bac Hong commune (chapter 4.2) was analysed. The classified satellite image was taken during the 3rd growing season when LCLU diversity was highest.

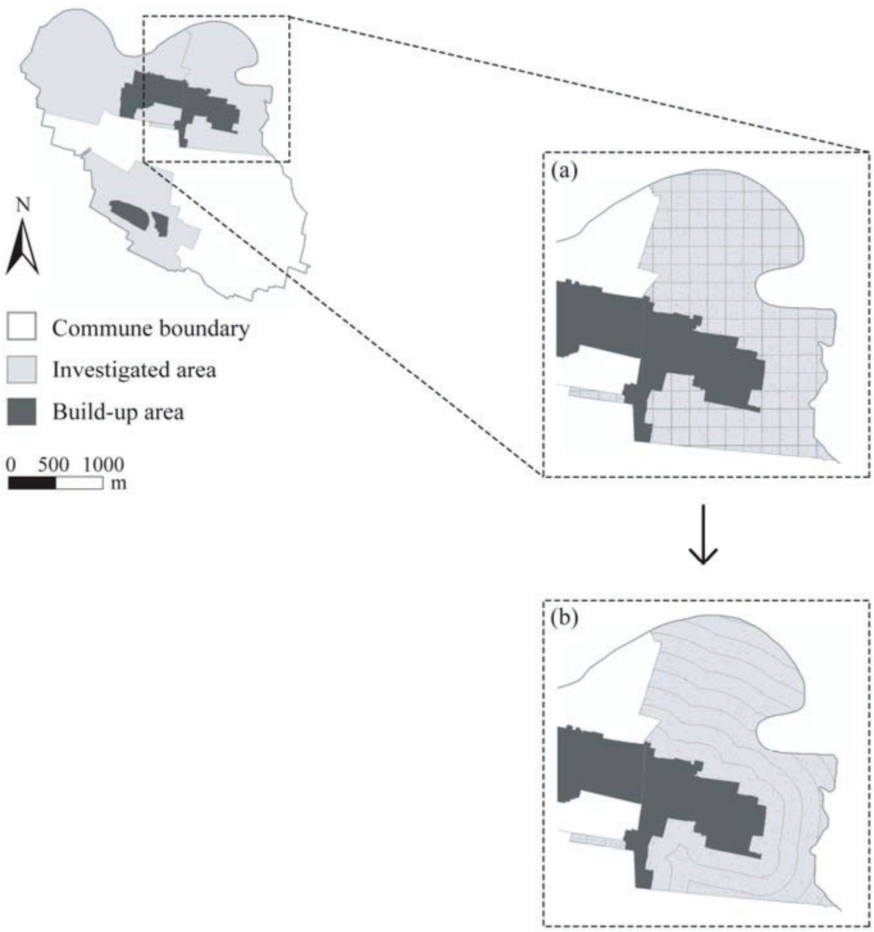

Fig. 1. The Bac Hong commune, the 100 × 100 m grid (a) and build-up buffer with 100 m distance intervals (b).

The communal area of the Thuy Ha, Thuong Phuc and Ben Chung villages was first stratified with a 100 × 100 m grid to ensure equal sampling across the entire village area (Fig. 1a). Five sample fields were randomly selected from each grid. In a second step, build-up buffer with a distance interval of 100 m was created and fields were labelled according to the respective buffers (Fig. 1b).

Table 1. Summary of explanatory variables used in cropping pattern analysis.

Variable Name		Type	Unit
Dependent variables			
Cash crops (i.e. maize, vegetables)		Categorical	0 – 1
Independent variables			
Buffer (1), built-up area - field	0 – 100 m	Categorical	0 – 1
Buffer (2)	100 – 200 m	Categorical	0 – 1
Buffer (3)	200 – 300 m	Categorical	0 – 1
Buffer (4)	300 – 400 m	Categorical	0 – 1
Buffer (5)	400 – 500 m	Categorical	0 – 1
Buffer (6)	500 – 600 m	Categorical	0 – 1
Buffer (7)	600 – 700 m	Categorical	0 – 1
Buffer (8)	700 – 800 m	Categorical	0 – 1
Buffer (9)	> 800 m	Categorical	0 – 1

Thus, fields were classified according to 9 buffers (Table 1). A total of 2081 fields were sampled from 8933 fields in the three villages. Similar to the procedure in chapter 2, maize and vegetables were grouped into cash crops, while fallow land remained fallow. The logistic regression procedure (Agresti, 2002; Hosmer and Lemeshow, 1989) was applied to analyse the probability of the categorical dichotomous outcome, explained by independent categorical buffer variables. Thereafter, performance of the model was verified by maximum likelihood estimates, standard error (S.E.), Wald statistic (χ^2) and the odds ratio (Agresti, 2002; Hosmer and Lemeshow, 1989). Nagelkerke's R^2_N was calculated as goodness-of-fit of the respective models (Nagelkerke, 1991). Furthermore, the ROC (Receiver Operation Characteristics) of the model was computed for possible cutoffs from 0 to 1 (Agresti, 2002). The area under curve (AUC) was also estimated. In this study, SPSS® software package was used for statistical analysis.

Results and Discussion

For maximum likelihood estimates of cash crop, the LCLU was compared to fallow LCLU. The analysis revealed a LCLU cash crop model containing 7 of the 9 initially introduced independent buffer variables (Table 2). Buffer distances proved significant ($P < 0.05$) and reached a reasonably good model fit with Nagelkerke's R^2_N (0.26) (Domencich and McFadden, 1975; Louviere et al., 2000). Independent variables were also tested for multicollinearity, but the values obtained were below the critical threshold.

Table 2. Maximum likelihood estimation for cash crops (i.e. maize, vegetables) in the 3rd cropping season.

Variable		Parameter estimate	S.E.	Wald (χ^2)	Sig.	Odds ratio
Buffer (1)	0 – 100 m	3.47	0.33	107.44	0.00	32.01
Buffer (2)	100 – 200 m	3.57	0.34	110.74	0.00	35.39
Buffer (3)	200 – 300 m	3.00	0.34	76.57	0.00	20.07
Buffer (4)	300 – 400 m	2.36	0.35	44.43	0.00	10.62
Buffer (5)	400 – 500 m	1.78	0.38	21.80	0.00	5.95
Buffer (6)	500 – 600 m	1.21	0.42	8.24	0.00	3.35
Buffer (7)	600 – 700 m	1.03	0.49	4.42	0.04	2.80
Constant		-3.43	0.32	113.78	0.00	0.03

Nagelkerke's $R^2_N = 0.26$

A classification table with cutoff values from 0 to 1 was calculated (Table 3). The overall percentage of correctly classified fields ranged between 56 and 70% and reached highest prediction at 0.5 cutoff value. At cutoff value 0.1, false negative prediction was lowest, but highest at 0.9 cutoff value. Conversely, false positive prediction was lowest at cutoff value 0.9 and highest at 0.1. A ROC curve was also drawn for the LCLU cash crop model (Fig. 2) and the AUC estimated (AUC = 0.75). The curve indicates a good performance according to Pontius Jr and Schneider (2001).

Table 3. Classification table for cash crops (i.e. maize, vegetables) in the 3rd cropping season.

Cutoff value	Overall percentage (%)	Specificity (%)	Sensitivity (%)	False negative prediction	False positive prediction
0.1	55.8	37.6	95	33	887
0.3	66.9	60	81.7	121	568
0.5	69.9	72.6	64.1	237	390
0.7	68.3	100	0	660	0
0.9	68.3	100	0	660	0

Regression coefficients were highest for fields in the first two buffers. Regression coefficients reduced with every additional buffer, and were lowest in buffer (7) and (8), respectively. Thus, the closer the field to the built-up area, the more likely for LCLU cash crop to occur.

Conversely, the more remote the field, the more likely it remained fallow during the 3rd growing season. The odds of finding LCLU cash crops were 32 and 35 times higher in the first two buffers than in buffer 9. The odds gradually reduced with additional buffers.

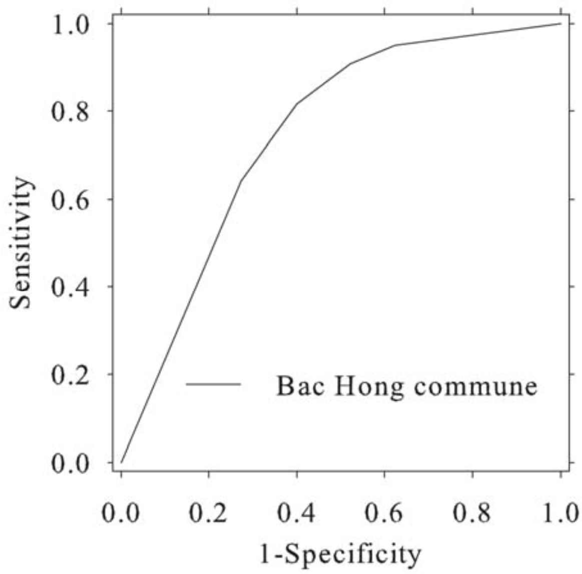

Fig. 2. ROC curve with AUC (0.75) for the LCLU cash crop model applied to the Bac Hong commune.

Performance of the LCLU cash crop model was similar to that of the built-up buffer crop rotation model presented in chapter 2. Informative value, overall correct prediction value and AUC were similar. The main difference was found with the number of independent built-up buffer variables included. While the built-up buffer crop rotation model in chapter 2 only included the first three buffers, the LCLU cash crop model included the first 7 buffers. This difference was mainly related to the comparatively large sample size in the LCLU cash crop model. Furthermore, soil fertility variables could not be included in the model, as detailed soil maps were not available.

Conclusion

The study proved that it is possible to develop statistical models from remote sensor LCLU data. Though the LCLU cash crop model does not provide temporal information, a similar performance supports the assumption that cash crops are generally grown close to the homestead or built-up area, while remote fields are left fallow or may be used for staple crop cultivation.

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Appendix 2: Glossary

ADS40	Air borne digital sensors that provides ground sampling distances down to 5 cm for panchromatic, multispectral and infrared bands.
Area sub-object: mean	Feature for labelling. Mean value of the areas of the sub-objects.
AUC	Area under curve is used in statistics. It is a combined measure of sensitivity and specificity. It is a measure of the overall performance of a model and can be interpreted as the average value of sensitivity for all possible values of specificity.
Bonferroni correction	Correction applied to the *α-level* to control the overall *Type I error rate* when multiple significance tests are carried out.
Buffer distance	Buffer distance, as defined in this work, is the distance from point A to point B expressed in distance buffers. It is implemented with the multiple buffer function in GIS.
Cash crops	Crop grown for profit usually sold on the market.
Classified as	The idea of this feature is to enable the user to refer to the classification of an image object without regard to the membership value.
Coefficients of variation	CV is a normalized measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation σ to the mean μ.
Colour/shape	Criterion used in segmentation that defines the textural homogeneity of the resulting image objects. In effect, by decreasing the value assigned to the Shape field, one defines to which percentage the spectral values of the image layers will contribute to the entire homogeneity

	criterion. This is weighted against the percentage of the shape homogeneity, which is defined in the Shape field.
Compactness/smoothness	The smoothness criterion is used to optimize image objects with regard to smoothness of borders. The compactness criterion is used to optimize image objects with regard to compactness. Increasing one criterion will reduce the other.
Covariates	Variable that is possibly predictive of the outcome under study. It can be of direct interest or it may be a confounding or interacting variable.
Crop rotation	Sequence of crops cultivated on the same portion of land until the rotation is repeated.
Cropping pattern	Allocation of land to particular crops that can differ according to farm type. Usually, they are associated with the spatial arrangement of crops on farms or in management units.
Cubic convolution filter kernel	Re-sampling procedure that determines the grey level from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates.
Denitrification	Biochemical reduction of nitrate to nitrite or gaseous nitrogen (N_2 or NO_x) resulting in the loss of nitrogen into the atmosphere.
Density of sub-object: mean	Feature used for labelling. Mean value calculated from the densities of the sub-objects. The density can be expressed by the area covered by the image object divided by its radius, which is approximated using the covariance matrix.
Deposition	Deposition as atmospheric deposition occurs as inorganic and organic nitrogen in precipitation or dry particulate matter.

Differential GPS	Enhanced global positioning system that uses the space-based global navigation satellite system and a network of fixed, ground-based reference stations to increase precision and reliability of positioning and navigation.
Digital elevation models	A digital map of the elevation of an area on the earth. Digital elevation models are gray scale images wherein the pixel values are actually elevation numbers.
Edge sharpener	In this study it is a filter which uses a subtractive smoothing method to sharpen an image. The edge sharpener starts with an averaging filter, subtracts the averaged image from the input image and ends by adding the image difference back to the original.
Effect size	Statistical measure of the strength of the relationship between two variables.
Euclidian distance	Direct distance between point A and B, usually calculated with the Euclidian function in the GIS software.
Existence of super-objects	Feature for labelling. It is the existence of an image object assigned to a defined class in a certain perimeter (in pixels) around the image object concerned.
Familywise error rate	Probability of making one or more false discoveries, or *type I errors* among all the hypotheses when performing multiple pairwise tests.
Farming system	Farming system is a complex inter-related matrix of soils, plants, animals, implements, labour and capital, inter-dependent farming enterprises.
Food security	Access by all people at all times to enough food for an active and healthy life.
Fuzzy classification	Classification based on fuzzy logic, which is a form of multi-valued logic derived from fuzzy set (sets whose

	elements have degrees of membership) theory to deal with reasoning that is approximate rather than precise.
GIS	Geographical Information Systems that allows spatial data from diverse sources to be combined and presented at different interdependent spatial layers.
GLCM entropy	Gray level co-occurrence matrix is a feature for labelling. It is a tabulation of how often different combinations of pixel gray levels occur in an image. A different co-occurrence matrix exists for each spatial relationship. The value for Entropy is high, if the elements of GLCM are distributed equally.
GLDV angular 2nd moment	Gray level difference vector is a feature for labelling. It is the sum of the diagonals of the GLCM. It counts the occurrence of references to the neighbor pixels' absolute differences. GLDV is high if some elements are large and the remaining ones are small.
Goodness-of-fit	Describes how well a statistical model fits a set of observations.
Ground control points	Reference points which are visible in imagery and which may be used to tie two or more images together and/or to a ground coordinate system.
Ground truth data	Information that is collected ‘on location’. The collection of ground-truth data enables calibration of remote-sensing data, and aids in the interpretation and analysis of what is being sensed.
High-pass filters	Filter that passes high frequencies well but attenuates (i.e., reduces the amplitude of) frequencies lower than the cutoff frequency.
Inorganic fertiliser nitrogen	Nitrogen in inorganic fertiliser such as urea, ammonium sulphate and NPK.

Kappa coefficient	Statistical measure of the agreement, beyond chance, between two maps (e.g. output map of classification and ground-truthed map).
Length/with	Feature for labelling. It is identical to the ratio of the eigenvalues of the covariance matrix with the larger eigenvalue being the numerator of the fraction.
Kruskal-Wallis test	The one-way analysis of variance by ranks is a non-parametric method for testing equality of population medians among groups.
Labelling algorithm	Labelling algorithms compute the membership value of an image object to one or more classes and modify the object classification based on this information.
Land cover	Land cover is the physical material at the surface of the earth. Land covers include grass, asphalt, trees, bare ground, water, etc.
Land use	Land use deals with the spatial aspects of all man's activities on land and the way in which the land surface is adapted to serve human needs.
Laplace Type I	Filter for edge detection. The filter with a weighted 3 × 3 filter window (0,1,0,1,-4,1,0,1,0) that sums up to zero.
Levene's test	Inferential statistic used to assess the equality of variance in different samples.
Life cycle assessment	Tools to assess the environmental impact of a product from cradle to grave. They can be used to calculate waste flows, resource consumption and environmental emission from waste management systems.
Liquid waste	Liquid waste usually originates from a community. It may be composed of domestic wastewaters or industrial discharges.

Logistic regression	Statistical technique to analyse the probability of a categorical dichotomous outcome, which is explained by a set of independent, continuous or categorical variables.
Log-likelihood	Summing the probabilities associated with the predicted and actual outcomes analogous to the residual sum of squares in multiple regression in the sense that it is an indicator of how much unexplained information there is after the model has been fitted.
Macro-nutrients	Chemical elements required by plants in relatively large amounts such as nitrogen, phosphorus or potassium.
Mann-Whitney test	Non-parametric test for assessing whether two independent samples of observations come from the same distribution.
Material flow analysis	Method can be used for a systematic assessment of the flows and stocks of material within a system defined in space and time. Results of MFA can be controlled by a simple material balance comparing all inputs, stocks, and outputs of a process.
Maximum difference	Feature for labelling. Minimum mean value belonging to an object is subtracted from its maximum value. To get the maximum and minimum value the means of all layers belonging to an object are compared with each other. Subsequently the result is divided by the brightness.
Maximum likelihood estimation	Statistical method used for fitting a statistical model to data, and providing estimates for the model's parameters.
Mean	In this case it is a feature for labelling. Layer mean value calculated from the layer values of all pixels forming an image object.
Mean sub-object: stdv.	Feature for labelling. Standard deviation of the different layer mean values of the sub-objects.

Micro-nutrients	Chemical elements such as Boron (B), Chlorine (CI), Copper (Cu), Iron (Fe), Manganese (Mn), Molybdenum (Mo), and Zinc (Zn), required only in small amounts by the plant.
Mixed pixels	Pixel that has a digital number which represents the average energy emitted or reflected from several different surfaces occurring within that area represented by the pixel.
Morphological features	Feature that analyses the shape of an object.
Multicollinearity	Statistical phenomenon, in which two or more predictor variables in a multiple regression model are highly correlated.
Multi-resolution segmentation	Segmentation that follows a hierarchical procedure starting with large segments. With every addition of a segmentation level, the size of the segments is reduced and the shape adjusted until the field size is reached. Segments of a lower segmentation level are child-objects of higher level objects.
Multi-spectral bands	Multi-spectral image with different layers such as for instance red, green, blue, near infrared (NIR).
Multi-temporal analysis	Spatially-explicit representation of change obtained when two maps or raster objects are compared to obtain a change between two points in time.
NDVI	Normalised Difference Vegetation Index is widely used for analysis of vegetation activity.
NIR	Electromagnetic radiation whose wavelength is longer than that of visible light (400–700 nm). Near infrared covers a range from 0.7 to 1.0 nm.
Nutrient balance	Nutrient balance refers to the nutrient difference between the sum of inputs and outputs.

Nutrient budget	Nutrient budget is a procedure that accounts for inputs and outputs of nutrients in a defined system.
Mass flows rate	Mass flow rate is the movement of mass per time. Its unit is mass divided by time.
Flux	The term nutrient flux is often used as mass flux, which is the rate of mass flow across a unit area ($kg \cdot m^{-2} \cdot s^{-1}$).
Object-based classification	Classification that consists of labelling homogeneous pixel groups (i.e. objects/segments). The input data first undergoes an automated segmentation process, which is based on the hypothesis that neighbouring image pixels belong to the same object. Neighbouring pixels are merged and grouped depending on homogeneity parameters.
Occurrence frequency	The number of times a given event occurs at specified sample points during a defined period.
Odds ratio	Indication of change in odds, given a unit change in the independent variable.
Organic fertiliser nitrogen	Nitrogen in organic fertiliser such as cattle, pig and poultry manure.
Organic matter	Matter that has come from a once-living organism and is composed of organic compounds. It is capable of decay, or the product of decomposition.
Overall accuracy	The percentage of correctly classified pixels.
Panchromatic bands	Black and white image, which has usually a higher resolution than multispectral bands.
Participatory Rural Appraisal	The Participatory Rural Appraisal is distinguished by the use of local graphic representations created by the community that legitimize local knowledge and promote empowerment.
Path distance	Path distance, as defined in this work, is the distance in meter from point A to point B. A path algorithm selects the

	optimal path according to different criteria such as for instance quality of road surface, length of road or elevation, using a road-path infrastructure network.
Per-field classification	Classification that consists of labelling homogeneous pixel groups (i.e. segments). Per-field vector and raster data are manually merged to segments in a geographical information system.
Pixel-based classification	Classification procedure that is based on statistical analysis of individual pixels.
Planned comparisons	Also called planned contrasts are theory-led comparison based on the idea of partitioning the variance created by the overall effect of group differences into gradually smaller portions of variance. They do not require post hoc tests.
Producer accuracy	Producer accuracy informs about the proportion of correctly labelled objects in the reference data. This is also a measure of omission errors.
Rank transformed ANCOVA	Statistical procedure that uses the F-ratio on rank transformed data to test the overall fit of a linear model controlling for the effect that one or more covariates have on the outcome variable.
Rapid Rural Appraisal	Series of techniques for ‘quick and dirty’ research that are claimed to generate results of less apparent precision, but greater evidential value, than classic quantitative survey techniques.
Rel. border to	Feature for labelling. It refers to the length of the shared border of neighboring image objects.
Relative elevation topography	Locally used terminology to evaluate the elevation of a field compared to neighbouring fields.

ROC	Receiver operation characteristics is a statistical measure. The curve displays sensitivity versus 1-specivicity for possible cutoffs from 0 to 1.
RS	Remote sensing is the science of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information.
Sapiro-Wilk test	Tests the null hypothesis that a sample $x_1, \ldots, x_n$ came from a normally distributed population.
Scale parameter	Determines the maximum allowed heterogeneity of the resulting image objects. In heterogeneous data the resulting objects for a given scale parameter are smaller than in more homogeneous data.
Segmentation	Neighbouring pixels are merged and grouped depending on homogeneity parameters. It is based on the hypothesis that neighbouring image pixels belong to the same object.
Sensitivity	Measures the proportion of actual positives outcomes which are correctly identified.
Single-resolution segmentation	Scale parameter settings best addressing field size and shape are selected and segmentation is executed in one pass.
Sobel Edge Detector	A filter for edge detection. The filter with a two weighted 3 $\times$ 3 filter window G_x (1,0,-1,2,0,-2, 1,0,-1) and G_y (1,2,1,0,0,0,-1,-2,-1).
Soil fertility	Ability of the soil to serve as a habitat for plants and to produce crops yields.
Solid waste	Non-liquid, non-soluble materials ranging from municipal garbage to industrial wastes.

Spatial resolution	A measure of the smallest area identifiable on an image as a discrete separate unit. In raster data, it is often expressed as the size of the raster cell.
Specificity	Measures the proportion of negatives outcomes which are correctly identified.
SSCM	Site-specific crop management is defined as matching resource application and agronomic practices with soil attributes and crop requirements.
SSNM	Site-specific nutrient management is the dynamic, field-specific management of nutrients in particular cropping seasons to optimize the supply and demand.
Staple crops	Typically inexpensive starchy foods crops that are high in energy and commonly served as part of every meal.
Test data	Data used in the assessment of classification accuracy.
Texture (soil)	Texture in terms of soil texture is a soil property used to describe the relative proportion clay, silt, and sand.
Texture feature	Feature that makes use of the variation in the grey values of adjacent pixels and their specific spatial arrangement.
Thematic object ID	The identification number (ID) of a thematic object.
Topological features	Features that relate the position of an object to another in the spatial context.
Training data	Data used in supervised methods of pattern recognition to ‘teach’ a classifier the main characteristics of each class.
Trajectory analysis	Successions of land-cover type for a give sampling unit over more than two observation years.
Type I error rate	Also called α *error*, is to reject the null hypothesis when the null hypothesis is true.

Urban and peri-urban agriculture	Urban and peri-urban agriculture is the production, processing and distribution of a diversity of food and non-food products within or at the fringe of an urban area.
User accuracy	User accuracy indicates the probability that a specifically labelled object also belongs to that specific class in reality. It reveals commission errors.
Volatilisation	Transition of either a liquid or a solid directly into vapour state as for instance ammonia volatilisation where nitrogen in a liquid or solid phase is converted to gaseous NH_3.
Wald statistic	Measure used to ascertain whether a variable is a significant predictor of the outcome.

Appendix 3: Acknowledgements

First of all I would like to thank Prof. Dr. Bernd Lennartz for giving me the opportunity to work on this highly interesting and challenging project, for his great support, the critical review, and the very constructive comments. I also would like to thank Mr Roland Schertenleib advisor of my dissertation and Mr Chris Zurbrügg Director of the Department of Water and Sanitation in Developing Countries (Sandec) at the Swiss Federal Institute of Aquatic Science and Technology (Eawag) for offering me to develop a small group on organic waste reuse in agriculture (formerly urban agriculture). The experiences I could gain especially in collaboration with Mr Noah Adamtey, Sandec-IWMI PhD, on his project 'Enrichment of recycled waste for peri-urban maize cultivation and its effects on the soil environment' were enriching and highly inspiring. Further, I would like to thank Prof. Dr. Harald Menzi, advisor of my dissertation, who always found time for discussions and visited me during my field study in Vietnam. I am also indebted to Dr. Tobias Kellenberger from the Swiss Federal Office of Topography (formerly University of Zurich) and to Mr Yves Buehler from the University of Zurich. They provided me office space, affiliated me to their group and coached me during the remote sensing analysis. It was a pleasure to work with them.

This project would not have been possible without the very good collaboration with our partners in Vietnam who participated in the case study. Especially Mr Vu Dinh Tuan, Mr Bui Tan Yen and Mr Dinh Viet Hung of the Soil and Fertiliser Insitute (SFI) I would like to mention. Mr Vu Dinh Tuan coordinated my visits and field surveys, Mr Bui Tan Yen supported the collection of geographical data and Mr Dinh Viet Hung joined me over the many months of survey in the peri-urban of Hanoi. Besides I would like to thank all those Vietnamese people, who supported the work in the one or the other way. It was a pleasure and an enriching experience to work with our Vietnamese partners.

Furthermore, I would like to thank Dr. Manouchehr Amini (Eawag) for the very interesting discussion regards statistical data analysis and modelling. I enjoyed very much to work with him and appreciated his critical, analytical thinking. Also, I would like thank Mr Christoph Speck for introducing me to advanced database management. I am still convinced, without the use of a professional database it would have been difficult to reach that far.

I would like to thank to Mr Sylvie Peter (Sandec editor/translator) for linguistic revisions of the thesis. I always liked her suggestions, which allowed to improve my writing skills.

Thanks go to all present or former Sandec colleagues who I met during the time of the project, who welcomed me every day and created the very nice working environment. Especially I would like to thank to Valérie Cavin, Caterina Dalla Torre, Stefan Diener, Prem Gurung, Doulaye Koné, Samuel Luzi, Christoph Lüthi, Sonko El hadji Mamadou, Mbaye Mbeguere, Regula Meierhofer, Antoine Morel, Marie-Madeleine Ngoutane, Atitaya Panuvatvanich, Sylvie Peter, Philippe Reymond, Silke Rothenberger, Monika Schaffner, Roland Schertenleib, Michael Steiner, Martin Strauss, Andrea Tamas, Elizabeth Tilley, Yvonne Vögeli, Martin Wegelin, Chris Zurbrügg.

Without any funds I never could have started this project. I gratefully acknowledge the financial support provided by the Swiss Agency for Development and Cooperation (SDC) and the Swiss National Science Foundation (SNSF) through the National Centre of Competence in Research (NCCR) North–South programme.

Finally, I would like to thank to my family which always supported me, whether I was steering through quiet water or through the rough, stormy sea.

Appendix 4: Selbständigkeitserklärung – Own work declaration

Ich erkläre, dass ich die hier vorgelegte Arbeit selbständig und ohne fremde Hilfe verfasst, andere als die von mir angegebenen Quellen und Hilfsmittel nicht benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

Ort/Datum	Unterschrift
22. Dezember 2009	Dionys Forster

Appendix 5: Theses for the dissertation

Title: Agricultural land use and associated nutrient flows in peri-urban production systems

Submitted by Dionys Forster

Theses are based on specific objectives and related research questions.

1. Similarities in land use practices of peri-urban agricultural production systems at farm and village level can be labelled as patterns, for which driving factors can be identified and characterised.

- Farming systems analysis of representative farms (34 farms), distributed over three villages in the peri-urban Bac Hong commune, provided information on spatially distinct land use practice over time. Agricultural diversity was addressed by semi-structured interview techniques, a tailored database system (MSAccess®) and a differential GPS system (Leica GS20®). The differential GPS system allowed to record field/plot size and different distance parameters (field – homestead). The environmental conditions (e.g. soil quality) and management practice of each field were discussed with the farmer.

- The logistic regression technique was used to develop spatially explicit crop rotation models. A total of 44 independent variables, such as path, Euclidian, buffer distances, road buffer, field size, soil fertility, water availability, topography, and livestock, were tested for their prediction effects on crop rotations. The SPSS® software package was used for statistical data analysis.

- Crop diversity over the three major growing seasons required land use to be recoded into simplified categories, such as cash crops (C), staple crops (S) and fallow land (F). Crop sequence over the year was subdivided into three main crop rotations labelled as SSF, SSC, CCC and accounting for 43, 27 and 12% of the surveyed fields.

- The results obtained revealed similar land use practices among the peri-urban agricultural production systems at farm and village level. These similarities were labelled as patterns, and the driving factors were identified and characterised. Of the 44 variables tested, 10 influenced significantly the presence/absence of a certain crop rotation pattern

(SSF, CCC or SSC). Distance to the field was a major informative variable. Besides, occurrence of crop rotation was rather influenced by perceived soil fertility. Models, such as the Euclidian and path intervals, performed better than the model based on built-up buffer.

- The results further revealed that intensity of crop rotations (i.e. more cash crops per year) decreased with distance to the field and low soil fertility. The likelihood of finding cash crop-based rotations (CCC) was highest on nearby fields with perceived high soil fertility. This likelihood decreased with additional distance and lower soil fertility. However, the likelihood for combined staple/cash crop rotations (SSC) increased. Finally, SSC rotation was replaced by staple crop-based rotation (SSF) on remote fields. CCC and SSC rotations were mainly separated by distance, whereas SSF and CCC or SSC were also separated by perceived soil fertility.

2. Distinct nutrient flows linked to land use patterns allow to establish nutrient budgets in peri-urban agricultural production systems at farm and village level.

- Nutrient flows were observed to change depending on the prevailing land use practice. Analysis of nutrient flows was thus closely linked to land use analysis, and data collection was based on farming system survey. Semi-structured interview techniques, the tailored system database (MSAccess®) and the differential GPS system (Leica GS20®) were also used to record environmental conditions and management practices of each field of the farms selected in the Bac Hong commune.

- Uncertainties in the nutrient budget assessment can be significant. To partially reduce uncertainty, focus was placed on nutrient inputs only. The element nitrogen was chosen as an indicator for the entire nutrient management system. To assess inputs to a specific crop, inorganic (*N_inorg*) and organic (*N_org*) fertiliser nitrogen applications were cumulated and resulted in total nitrogen input (IN_{tot}) per field and crop rotation.

- Collected data was grouped into staple crop-based (SSF) rotation, cash crop-accentuated (SSC) and cash crop-dominated (CCC) rotations. Furthermore, data was computed for a combined rotation (SSC & CCC), including data for both SSC and CCC rotation. In a first step, inorganic, organic and total nitrogen inputs from crop rotations were compared.

The planned comparison first evaluated the SSF rotation with the combined SSC & CCC rotation. A comparison of SSC and CCC was subsequently conducted.

- In the second step, rank transformed ANCOVA was applied to explore the effects of different explanatory variables, such as buffer distance, road buffer, field size, soil fertility, water availability, topography, and livestock on average organic, inorganic and total nitrogen fertilisers used in crop rotations. In the last step, three major crops (i.e. paddy rice, maize, *Brassica oleraceae*) were analysed for differences in nitrogen inputs. The SPSS® software package was used for statistical data analysis.

- The results revealed distinct nutrient flows in land use patterns. However, complete nutrient budgets could not be established for reasons of data uncertainty. Nitrogen input proved suitable as an indicator for nutrient management. In the first planned comparison, nitrogen inputs for SSC & CCC were found to be higher and considerably different from SSF. Conversely, in the second planned comparison, only total nitrogen input for CCC was found to be higher and notably different from SSC.

- The results further revealed that the covariates of built-up buffer distance, plot size and soil fertility partially explained the variation in inorganic and total fertiliser inputs for the SSC & CCC rotation. Though the latter covariates reached large effect sizes, their overall informative value was low to moderate, reaching a highest value of 51% for the SSC & CCC rotation.

- The remaining variation in rotation was greatly affected by different crop fertiliser application patterns. Mean total nitrogen inputs differed significantly and were highest for maize followed by *B. oleraceae* crops and paddy rice.

3. Remote sensing (RS) and geographical information systems (GIS) contribute to assessing land cover/land use and improving identification of land use patterns at field, village and communal level. In this case, the argumentation was subdivided into parts A and B, as two different studies were carried out.

   Part A

   - RS and GIS contributed to assessing land cover/land use (LCLU). Crop, field size and location are, *inter alia*, factors driving farmers' decisions with regard to resource use (e.g. fertiliser management). Thus, identification of crops and cropping area are important steps when assessing the prevailing farming systems. Object-based classification of high spatial resolution satellite data is suggested for LCLU assessment of small-scale diversified landscapes.

- Object-based classification methods use a segmentation approach prior to classification. Segmentation algorithms producing homogeneous objects with distinct crop characteristics facilitate the classification process. Development of a segmentation procedure to obtain homogeneous and optimally sized segments requires experience and knowledge of local LCLU.

- An archived Quickbird image (acquisition date 8th Dec. 2004), with a panchromatic band of 0.6 m and four spectral bands of 2.4 m spatial resolution, was ordered for the project area. The panchromatic band was scaled to 0.5 m and the multi-spectral bands to 2 m spatial resolution. It was geo-referenced using a second order polynomial transformation and in-situ GPS measurements.

- The object-based image analysis software Definiens Professional® was used for land use/land cover analysis. The LCLU classification nomenclature followed a hierarchical classification into two categories ‘water’ and ‘land’ on the first level. On the second level, land was subdivided into ‘built-up&residential’ and ‘agriculture’. On the third classification level, agriculture was subdivided into seven categories, i.e. bare soil, fallow, maize, sweet potato, orchard, tree/hedge, and unclassified. Shape, texture, neighbourhood relationship were used in addition to panchromatic and multi-spectral data to build semantic network structures for classification purposes.

- According to the results, insufficient segmentation limited the potential of spectral, textural, morphological, and topological features used for labelling/classification. Since segmentation proved insufficient despite numerous attempts, objects, accentuating size and shape of fields were only partially reached. Even a high weighting of the panchromatic band did not allow extraction of visually distinctive field boundaries.

- Therefore, classification results had to be evaluated on the basis of a moderate segmentation. While some categories revealed low producer or user accuracy, the overall accuracy of 67% was still above average and the kappa coefficient provided good classification results.

Part B

- Since segmentation of small-scale diversified agricultural land presents a challenge and can affect classification quality, use of image pre-processing techniques (i.e. HPF), filters and multi-resolution region growing could improve segmentation and, thus, also image classification.

- Accuracy of field boundary delineation was usually assessed by a qualitative visual comparison. With increasing area and decreasing field size, qualitative evaluation of field boundary delineation became difficult and required quantitatively accurate measurements. In classification-based field boundary accuracy assessment, automated segmentation (e.g. single-/multi-resolution segmentation) was compared to per-field vector segmentation by classification and accuracy assessment based on an error matrix.

- As for part A, an archived Quickbird image (acquisition date 8th Dec. 2004) was purchased and pre-processed accordingly. Due to the small-scale diversity of local LCLU, segmentation was limited to the spatially best resolution panchromatic band. For improved delineation of single objects, two different HPF, the Laplace Type I and an edge sharpener were applied to the panchromatic band.

- Performance of the panchromatic band, edge sharpened band and Laplace filtered band for three different field boundary delineation approaches was subsequently evaluated. Moreover, 'single-resolution' and 'multi-resolution' segmentation was performed. A polygon per-field vector layer was then created by manual digitisation of field boundaries in GIS. It was used for per-field classification and considered as the best ground reference.

- The results revealed that internal variability of high spatial resolution data increased with peri-urban agricultural diversity and presented a challenge for LCLU classification. Additional pre-processing (i.e. high-pass filters) hardly improved field boundary delineation and, thus, classification accuracy. A comparison of the object-oriented and per-field agricultural LCLU classification methods indicated that the per-field classification method was far more adapted to this diversified, small-scale agricultural pattern. Per-field vector segmentation and classification results were far more accurate, achieving an overall accuracy of 83% and a kappa coefficient of 0.7 using pan, filtered pan, NDVI, green and blue band values, as well as band variables.

4. Use of the outputs of objectives 1 to 3 in the methodological approach improves upscaling of nutrient flows and budgets from field to village and communal level.

   - Though existing methods and tools provide a good overview of the flows of a city or town, they usually neglected the important spatial component. With regard to the management of waste flows, the spatial component is crucial, as economic scenarios are calculated on the basis of geographical determinants. Furthermore, agricultural landscapes can be highly diverse and vary over space and time. Thus, when developing waste management scenarios, great attention has to be paid to the agricultural system in place, with special emphasis on nutrient flows to avoid surplus application of fertilisers leading to environmental pollution.

   - The methodological approach was fist based on three analytical steps, followed by a process of crop rotation modelling, a process of nutrient flow modelling and, finally, a process to develop waste reuse scenarios at village and communal level. In the first step of analytical procedure, a broad picture is obtained of the prevailing farming systems, with special focus on land use. It comprises map surveys, collection of statistical data, expert interviews, farmer group discussions, and transect walks. The second step aims at exploring possible spatial and temporal patterns in the cropping systems and corresponding nutrient flows. It includes farm sampling, farm survey, data pre-processing and statistical analysis. In the third step, land cover/land use is assessed by remote sensing (RS) and GIS.

   - Modelling of crop rotations is strongly dependent on the variables pertaining to the likelihood of crop rotations to occur. Thus, the data required can differ from one region to another. In the presented example, modelling of crop rotations required distance and soil fertility. The multiple buffer function in GIS assists in creating distance intervals. Soil fertility can be retrieved from farmers' participatory soil fertility mapping or from a detailed official soil fertility map. Data is then transformed into GIS-raster layers. Based on the statistical model developed in the analytical step 2, the likelihood of a specific crop rotation to occur is predicted and transcribed into each grid cell.

   - Where soil fertility maps are unavailable or where the degree of detail is insufficient, modelling of crop rotations may be based on distance and land cover/land use data. Distance intervals are first used to predict the likelihood of a specific crop rotation to occur. The highest likelihood again determines the rotation. Land cover/land use information is then used to adapt the crop rotation to the actual land use in place.

- Modelling of nutrient flows is determined by the respective crop rotation, and corresponding models developed as in analytical step 2. In the presented example, the variables of built-up buffer distance, soil fertility and plot size play a key role in predicting flows and are transformed into GIS-raster layers. The model then predicts input flows based on given variables, of which those are selected corresponding to the consolidated crop rotation. Also output flows could be linked to crop rotation, followed by computation of spatially explicit nutrient budgets. As an alternative to the analysis of output flows, inputs to crop rotations may be compared with the fertiliser recommendations.

- Development of organic waste reuse scenarios at village and communal level require knowledge of spatial-temporal nutrient flows. The objective is to assess the amount of nutrients supplied to the commune by taking into account the amount already applied by the farmer. As availability and access to inorganic fertiliser is usually good and surplus application frequent in peri-urban areas, potential organic waste reuse could be considered where inorganic fertilisers are replaceable.

- As only nutrient aspects are considered so far, aspects of waste quality should also be included in the development of waste reuse scenarios. Since the organic waste (solid or liquid) quality can vary considerably, spatially explicit crop rotations and remote sensing data could provide information on spatial and temporal cropping patterns and, thus, contribute to delineating waste reuse restriction areas.

- Information on spatially explicit crop rotations and associated nutrient flows can also provide planning base for decentralised waste treatment. Where the reuse potential is high, planning may consider the construction of treatment facilities (e.g. sludge treatment plants or co-composting units). Furthermore, transport costs can be kept low, as spatial assessment of nutrient flows allows to optimise waste transport logistics.