DISS. ETH NO. 21980

# MULTI-LEVEL ASSESSMENT OF LAND DEGRADATION: THE CASE OF VIETNAM

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH

(Dr. Sc. ETH Zurich)

presented by

MANH QUYET VU

Master of Sciences, Bonn University, Germany

born on May 2, 1976

citizen of Vietnam

accepted on the recommendation of

Prof. Dr. Emmanuel Frossard, main supervisor

Dr. Quang Bao Le, co-examiner

Prof. Dr. Paul. L.G. Vlek, co-examiner

Prof. Dr. Rainer Schulin, co-examiner

2014

DEDICATION

To my family with respectful gratitude

My wife Tran Thi Thuy Thuy
My daughter Vu Tran Minh Trang
My son Vu Duc Minh.

## Remarks

This is a cumulative thesis consisting of three research papers, which were contributed to by several authors and I was the leading author. The figure, table numbering of three papers (Chapter 2, 3 and 4) were adjusted for consistence with the whole dissertation. All references of three chapters were given at the end of the thesis. For the consistency, I use the personal pronoun 'we' throughout this thesis, even though the chapters *Introduction* and *Concluding remarks*, are authored by me alone.

## Summary

Land degradation, defined as a persistent decline of the biological productivity of the land, has attracted the attention of researchers and policy-makers worldwide. Today, about one-quarter of the global land mass is degraded. Agricultural and rural development without further land degradation is essential for nations whose economy relies heavily on agriculture such as Vietnam. As land degradation is driven by natural and human factors acting over multiple scales in time and space, understanding the phenomenon needs a multi-scale approach. Such an approach bears also the potential to inform scale-specific land management objectives. Very few works have assessed land degradation with a multi-scale approach.

The present study aims at assessing land degradation from national to farm scales through a multi-level framework. The general question is how can we organize scale-specific land degradation assessments and integrate them to generate knowledge for informing policies combating land degradation. This thesis addresses this question using Vietnam as a study case. The results of the research are reported in three chapters. The geographic hotspots of land degradation are identified and characterized at national level in the first chapter. The following chapter identifies the social, economic and biophysical factors affecting land degradation, and quantifies their directions and weights. At the level of identified hotspots it is necessary to understand what constrains farmers to adopt suitable management practices. Thus, the third main chapter evaluates social–ecological factors constraining the adoption of fertilizer and manure use at farm level.

The first chapter delineates the geographic hotspots of human-induced land degradation in the country and classifies the social–ecological characterization of each specific degradation hotspot type. The research entailed a long-term time-series of Normalized Difference Vegetation Index (NDVI) to specify the extent of areas with significant biomass decline or increase in Vietnam. Annual rainfall and temperature time-series were then used to separate areas of human-induced biomass productivity decline from those driven by climate. Next, spatial cluster analyses identified social–ecological types of degradation for guiding further investigations at regional and local scales. The results show that about 19% of the national land mass experienced persistent declines in biomass productivity over the last 25 years. We identified six and five social–ecological types of degradation hotspots in agricultural and forested zones, respectively. These hotspot types exhibit different social and ecological conditions, suggesting that region-specific strategies are needed for the formulation of land degradation combating policies.

In the second chapter, we identified and characterized the biophysical and socio-economic factors that affect significantly land degradation across Vietnam. The hypothesized explanatory variables were common economic and demographic drivers and bio-physical factors such as soil constraints, and neighborhood land-use structures that are often neglected in large-scale land degradation assessments. Instead of using a single inferential statistic technique, we used multi-linear regression and binary logistic regression in a complementary manner to increase the detectability and credibility of the degradation causes. The results showed that agricultural production growth had strong and consistent effects on land degradation extent and intensity. The presence of a neighboring forest was shown to reduce land degradation intensity in abandoned, unproductive lands. The results have implications for national land management policies: i) internalizing land degradation costs in the farming system analysis and evaluation of payment for ecosystem services policy, ii) restricting forest conversion, and iii) improving extension services and education in agrarian communities.

The third chapter selected the Yen Chau district of Son La province – located within the most degraded and poorest zone identified by the first chapter - as a study case. One of the main problems accounting for the degradation of agricultural land is prolonged nutrient mining by crops due to insufficient inputs of mineral fertilizers and manures. Thus, the chapter aimed at identifying socio-ecological types of households/farms and evaluating factors constraining/promoting smallholders' adoption of mineral fertilizer and manure uses. We defined six distinct smallholder farm types using Principal Component Analysis (PCA) and K-Means Cluster Analysis (K-CA). Then, we identified social, economic and ecological factors affecting farmers' decisions about mineral fertilizer (NPK compound) use and manure adoption, using regression analyses. We found that farmers' decisions with respect to mineral fertilizer and manure uses varied with the farm type. This implies that nutrient management policies need to be sensitive to specific farm types.

This thesis demonstrates that a multi-level assessment framework of land degradation combining complementary methods and data sources can deliver knowledge relevant to scale-specific policy/management needs. At each level, the framework focuses on different indicators of land degradation according to concerns of different stakeholder groups. The framework is flexible and can be adapted to other regions. It can also be incorporated in other assessments to develop an integrated tool for sustainable resource management. Since land degradation involves the combination of many complicated processes, further research should focus on different levels, indicators and the linkages between them to provide better and updated information as a basis for land degradation combating policy.

.

# Résumé

La dégradation des terres, définie comme un déclin persistant de la productivité des terres induit par l'homme, a attiré l'attention des chercheurs et décideurs politiques à travers le monde. Aujourd'hui, près d'un quart de la masse totale des terres est dégradé. Un développement agricole et rural sans dégradation est particulièrement important pour les pays fortement dépendants de l'agriculture tels que le Vietnam. Comme la dégradation des terres est le résultat de facteurs naturels et humains s'exerçant à différentes échelles de temps et d'espace, la compréhension d'un tel phénomène nécessite une approche multi-niveaux. Une telle approche donne aussi la possibilité de renseigner les objectifs de gestion des terres propres à chaque échelle. Il existe très peu d'études faisant appel à une approche multi-niveaux pour évaluer la dégradation des terres.

La présente étude vise à évaluer les phénomènes de dégradation des terres de l'échelon national à celui des exploitations agricoles au moyen d'une approche multi-niveaux. La question générale est comment peut-on organiser les évaluations propres à chaque niveau de la dégradation des terres et les intégrer pour générer un savoir à même de renseigner la formulation de politiques de réduction de la dégradation des terres. La thèse traite de cette question en utilisant le Vietnam comme cas d'étude. Les résultats de la recherche sont présentés dans trois chapitres. Les points chauds géographiques de la dégradation des terres sont identifiés et caractérisés à l'échelon national dans le premier chapitre. Le chapitre suivant met en avant les facteurs sociaux, économiques et biophysiques de la dégradation des terres et la quantification de leur direction et poids. Au niveau des points chauds identifiés, il est nécessaire de comprendre ce qui restreint les paysans dans l'adoption de pratiques de gestion appropriées. Ainsi, le troisième chapitre présente l'évaluation des facteurs socio-écologiques limitant l'utilisation d'engrais et de purin au niveau des exploitations agricoles.

Le premier chapitre délimite les points chauds géographiques de la dégradation des terres induite par l'homme au Vietnam et propose une classification des propriétés socio-écologiques de chaque type spécifique de point chaud de la dégradation. L'étude comprend une série chronologique à long terme de l'Indice de la Végétation par Différence Normalisée (NDVI) afin de révéler l'étendue des zones à déclin ou accroissement significatif de la biomasse. Les séries chronologiques de précipitations et températures annuelles ont ensuite permis de séparer les zones dont le déclin de la productivité était induit par l'homme de celles dont la dégradation résulte du climat. Ensuite, les classifications spatiales ont révélé les types socio-écologiques de la dégradation pour guider les investigations suivantes aux échelles régionale et locale. Les résultats montrent que, si l'on considère la productivité de la biomasse, le pays a vu quelque 19% de sa masse de terre se dégrader de manière persistante au cours des dernières 25 années. Nous avons identifié six et cinq types socio-écologiques de points chauds de la dégradation en zones agricoles et forestières, respectivement. Ces types de points chauds présentent différentes conditions sociales et écologiques, d'où la recommandation que des stratégies régionales sont requises pour formuler des politiques de lutte contre la dégradation des terres.

Dans le deuxième chapitre, nous avons identifié et caractérisé les facteurs biophysiques et économiques influençant de manière significative la dégradation des terres au Vietnam. Les variables explicatives testées étaient les éléments économiques et démographiques communs et les facteurs biophysiques tels que la pédologie, les contraintes topographiques et les structures d'affectation des terres avoisinantes qui sont souvent négligées dans de nombreuses évaluations à large échelle de la dégradation des terres. Au lieu d'utiliser une seule technique de statistique déductive, nous avons utilisé la régression linéaire multiple et la régression binaire logistique de manière complémentaire afin d'augmenter la détectabilité et la crédibilité des causes de la

dégradation. Les résultats ont montré que la croissance de la production agricole a eu des effets importants et cohérents sur l'étendue et l'intensité de la dégradation des terres. Il a été démontré que la présence d'une forêt avoisinante réduit l'intensité de la dégradation des terres dans les friches improductives. Les résultats sont autant d'implications pour la politique nationale de gestion des terres : (i) internalisation des coûts de dégradation des terres dans l'évaluation du système agricole en vue de la politique de paiement en contrepartie de services écosystémiques, (ii) limitation de la reconversion de la forêt en terres agricoles et de l'amélioration de l'extension des services et (iii) éducation dans les communautés agricoles.

Dans le troisième article, le district de Yen Chau de la province de Son La – située dans la zone la plus pauvre et présentant la plus forte dégradation identifiée dans le premier chapitre – a été sélectionnée comme cas d'étude. Une des causes principales de la dégradation des terres agricoles est l'extraction pérenne d'éléments nutritifs par des cultures du fait de l'insuffisance d'intrants d'engrais minéraux et de fumier. Ainsi, le chapitre visait à identifier les types socio-écologiques de ménages/exploitations agricoles et évaluer les facteurs de l'adhésion des petits propriétaires à l'utilisation d'engrais et de fumier. Nous avons défini six types de petites exploitations agricoles en utilisant l'Analyse en Composantes Principales (ACP) et l'algorithme des k-moyennes. Ensuite, nous avons identifié les éléments sociaux, économiques et écologiques influençant les décisions des paysans en ce qui concerne l'utilisation d'engrais chimiques (composés NPK) et du fumier au moyen d'analyses de régression. Nous avons constaté que les décisions des paysans en matière d'utilisation d'engrais minéraux et de fumier varient en fonction du type d'exploitation. Cela implique que les politiques de gestion des éléments nutritifs doivent tenir compte des types d'exploitation.

Cette thèse démontre qu'une approche multi-niveaux d'évaluation faisant appel à des méthodes et des sources de données complémentaires peut générer un savoir pertinent pour les politiques (ou la gestion) propres à chaque échelle. A chaque échelon, l'approche permet de se concentrer sur différents indicateurs de la dégradation des terres relatifs à différentes parties intéressées. L'approche est flexible et peut être adaptée à d'autres régions. Il est aussi possible de l'inclure à d'autres évaluations afin de développer un outil intégré pour la gestion soutenable des ressources. Puisque la dégradation des terres implique les effets conjugués de nombreux processus complexes, la recherche à venir devrait se concentrer sur différents niveaux, indicateurs et liens entre ces derniers pour informer de manière plus complète et actualisée les politiques de lutte contre la dégradation des terres.

# Table of contents

## List of tables

## List of figures

# 1. Introduction

## 1.1 Problem statement

The World Commission on Environment and Development (WCED) report (1987) entitled "Our Common Future" defined sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (p. 41). Land is an essential natural resource that cannot be replaced for every living activity (Food and Agriculture Organization [FAO], 1999). 'Land', understood as land ecosystem, includes not only the soil resources, but also the water, vegetation, landscape, and microclimatic components of a terrestrial ecosystem (Millennium Ecosystem Assessment [MEA], 2005; Scherr and Yadav, 1996). Sustainable development requires the maintenance and enhancement of land ecosystem functions and services to meet future demands.

According to the internationally authoritative definition given by United Nations Convention to Combat Desertification[1] - UNCCD (UNCCD, 2004) and MEA (MEA, 2005), land degradation is understood as the persistent reduction or loss of land ecosystem services, notably the primary production service (Safriel, 2007; Vogt et al., 2011). There are a number of important points in this definition. First, the term 'persistent reduction or loss' distinguishes land degradation from the fluctuations (e.g., seasonality) of terrestrial biological productivity. Land degradation takes place only if the biological production of the land does not return to the expected levels after the stress factors are removed or if a downward spiral of productivity occurs. Second, this definition focuses on land ecosystem services: land degradation makes therefore sense in the context of human benefits derived from land ecosystems uses. Negative changes in soil, water and vegetation resources are concerned as much as how seriously these changes will reduce supporting (e.g., primary production), provisioning (e.g., foods and other biomass-based products) and regulating (e.g., carbon sequestration) services provided by the land. Finally, the definition emphasizes the pivotal role of primary production because primary production is the basis of other ecological services (MEA, 2005; Safriel, 2007).

Land degradation has been, and still is a global problem (Von Braun & Gerber, 2012; Lal et al., 2012; Eswaran et al., 2001). Although the estimated area of global degraded land varies among different studies, a generally agreed figure is that about a quarter of global area has been degraded over the past three decades (Lal et al., 2012; Von Braun et al., 2012). This massive land degradation threatens global development goals, especially those related to global food security and rural poverty reduction (GEF, 2006; Jansa et al., 2010). Degradation of existing agricultural land reduces food production, and thus negatively affects food security (Eswaran et al., 2001; Stocking and Murnaghan, 2001). The increasing food demand of growing global population will continue causing a high pressure on land resources (Foley et al., 2011; Mueller et al., 2012; Tilman et al., 2011). Land degradation is most serious in tropical regions, where human livelihood relies heavily on agricultural production. In tropical areas, there is often a downward spiral between poverty and land degradation: poverty and economic marginalization lead to over exploitation of land resources resulting in land degradation, and land degradation leads to more serious poverty (Scherr, 2000).

[1] Desertification is defined by the United Nations Convention to Combat Desertification as “land degradation in arid, semiarid and dry subhumid areas resulting from various factors, including climatic variations and human activities”.

Land degradation is caused by both natural and anthropogenic factors (Von Braun and Gerber, 2012; Vlek et al., 2010). Typical examples of natural causes of land degradation are frequent or prolonged droughts, or high rainfall on sloping land. Anthropogenic causes of land degradation are more complex, including a hierarchy of intermediate causes (e.g., deforestation, overgrazing, shifting cultivation with shorten fallow periods and unbalanced fertilizer use) and underlying causes (e.g., population pressure, unsuitable land tenure regime and poverty) (Geist and Lambin, 2002; Nkonya et al., 2011a; Von Braun and Gerber, 2012). Although anthropogenic (or human-induced) land degradation can be theoretically mitigated, it seems a difficult task (Stocking and Murnaghan, 2001; Jansa et al., 2010; Foley et al., 2011).

Vietnam can be seen as a prevailing case of anthropogenic land degradation. The agricultural sector is still the main contributor to the economy in Vietnam. About 58% of the national population works in agriculture, forestry, and fishing activities (General Statistics Office [GSO], 2012); therefore, land plays an important role in the people’s livelihood. The agricultural sector provides not only the food but is also the basis for industrialization and other development processes seen as strategic by the government. Agricultural land area per capita is, on average, about 0.11 ha/person (GSO, 2012). Given this high land pressure, land degradation is one of the most striking problems for the nation. Recent expert-based estimation suggests that about 9.3 million ha of national land (28% of the total surface) has been affected by different forms of land degradation, of which 2.0 million ha of land have been seriously degraded (National Action Program to Combat Desertification [NAP], 2006). A rough estimate suggested that the livelihoods of about 22 million people have been influenced by land degradation (Cooke and Toda, 2008).

To combat land degradation on large scales (e.g., global, regional or national) policy makers need information on severely degraded areas to prioritize budgets for comprehensive, intensive research and mitigate interventions that can only be implemented at local levels (Le et al., 2012b; Vogt et al., 2011). Formulating effective policies to combat land degradation also requires the identification of the anthropogenic causes of the phenomenon (Vlek et al., 2008, 2010; Von Braun and Gerber, 2012). Although the categories of land degradation causes have been reviewed (Geist and Lambin, 2002; Nkonya et al., 2011a), comprehensive portfolios of the nation/region-specific causes and the understanding of their causalities are still lacking (Von Braun and Gerber, 2012). Although a great deal of knowledge exist on techniques that could be implemented to mitigate land degradation (e.g., Roy et al., 2006), low farmer adoption of these management practices remains a key bottle-neck for making real progresses in combating land degradation (Nkonya et al., 2011a).

## 1.2 Current state of the research field

### 1.2.1 Current approaches in land assessment

#### 1.2.1.1 Land degradation assessment based on expert-based soil degradation assessment

In the 1990s, the scope of land degradation research relied on soil degradation assessment. On a global scale, the Global Assessment of Human-induced Soil Degradation (GLASOD) (Oldeman et al., 1991) was the first worldwide assessment of soil degradation and remains currently the only uniform and primary global source of soil degradation data (FAO, 2000). A map on soil degradation severity on an average scale of 1:10 million was prepared based on expert judgment of a few hundred scientists. The soil degradation severity was estimated soil degradation intensity and extent. Soil degradation intensity was measured in a qualitative scale (i.e., light, moderate, strong, and extreme) by experts' opinions. Soil degradation extent was quantified by the percentage of degraded land area compared to the total area of administration unit (i.e., 0–5%, 6–10%, 11–25%, 26–50%, and > 50%) (Oldeman et al., 1991). Studies were also carried out at the regional level such as the "Digital geo-referenced database of soil degradation in Russia" (Stolbovoi and Fischer, 1997) and the "Soil degradation assessment in Central and Eastern Europe" (part of the Mapping of Soil and Terrain Vulnerability in Central and Eastern Europe [SOVEUR] project) (van Lynden, 2000). Methodologically similar to the GLASOD study, the Assessment of the Status of Human-Induced Soil Degradation in South and South East Asia (ASSOD) covered only soil degradation (van Lynden and Oldeman, 1997). The ASSOD data included a more detailed scale (1:1.5 million) for 17 countries in South and Southeast Asia, which assessed major soil degradation types (e.g., water erosion, wind erosion, chemical deterioration) and subtypes (e.g., loss of topsoil and terrain deformation, salinization). The degree of soil degradation was presented in qualitative terms as an impact on productivity (i.e., negligible, light, moderate, strong, and extreme impact). This may be taken as a reference for a national-level study, given that no better data exist.

Furthermore, the World Atlas of Desertification (Middleton and Thomas, 1997), based on the results of the GLASOD and ASSOD studies, included some readily available, country-level data on desertification. With the soil-based approach, it is difficult to draw reliable results on a large-scale and long-term basis due to the lack of soil data on such spatial and temporal scales.

On the national scale, the UNCCD is another source of expert-based data on soil degradation in dry lands provided by countries' reports. Some reports also include data on the current status of degradation. For example, the status of soil degradation in Vietnam in 2000, 2002, and 2006 can be drawn from its national report submitted to the UNCCD (http://www.unccd-prais.com/Data/Reports — Data accessed on May 31 2014 ).

The approaches used by the above-mentioned studies have limitations. First, as soil is only a subset of land, land degradation assessment based only on soil degradation ignores the declines of other important components of the land such as vegetation and biodiversity. Next, the expert-based assessment is necessarily subjective and cannot be used in regular quantitative monitoring over time. The assessments are also stratified by administration boundaries, not yet spatially explicit beyond these (Vogt et al., 2011). Because soil data that are explicitly measured in temporal and spatial terms are lacking, it is difficult to use the soil-centric approach over space and time. Finally, all of the expert-based, soil degradation assessments mentioned above were conducted in the 1980s or 1990s, thus are now outdated for supporting land use and management policies.

#### 1.2.1.2 Remote sensed land degradation assessment using vegetation productivity indices

With the available satellite time-series for monitoring the vegetation status over large areas, the vegetation-based approach has been recently used for global, continental, and national assessments of land degradation. With this approach, land degradation is measured by the persistent “change in net primary productivity (NPP) with deviation from the norm taken as indicators of land degradation or improvement” (Bai et al., 2008a). The Normalized Difference Vegetation Index (NDVI), a remotely sensed signal, is often used for approximately indicating the NPP of the land. Current satellite datasets offer the NDVI time-series for the entire globe over the last 30 years. Vlek et al. (2008, 2010) analyzed long-term NDVI trends in relation to the inter-annual dynamics of rainfall and atmospheric fertilization in order to determine the extent to which humans affect the NPP. "By relating these hotspot areas in sub-Saharan Africa with different attributes of the region such as population density, soil/terrain conditions and land-cover types, it is possible to surmise which underlying processes, e.g., deforestation or soil degradation, are at play" (Vlek et al., 2010, p. 60).

Recent studies on national, regional, and global scales assessed land degradation by measuring persistent change in the NPP, approximated by NDVI trends (Bai et al., 2008a; Vlek et al., 2008, 2010). In a recent research under the Land Degradation Assessment in Drylands (LADA) project, the present global assessment used remote sensing to identify areas where significant biological change is happening. The Global Assessment of Land Degradation and Improvement (GLADA), as part of the LADA project, has assessed land degradation by measuring changes in biomass production through remote sensing in some countries: Kenya, China, Tunisia, Argentina, Senegal, Cuba, and South Africa. Symeonakis and Drake (2004) combined four indicators—vegetation cover characteristics (NDVI), soil erosion, rain use efficiency (RUE), and surface runoff—in their research on monitoring desertification and land degradation over sub-Saharan Africa. Results showed that by integrating NDVI data with ancillary data (including land cover, ecological zones, topography, soil, and human and livestock populations), land degradation was attributed to both demographic pressure and biophysical factors (Vlek et al., 2008, 2010).

Most of the large-scale, land degradation assessments are still in the monitoring stage; quantifying the magnitude of the phenomenon has not yet objectively explained the causes or drivers of land degradation. Vlek et al. (2008, 2010) applied a step-wise analysis to show the potential relationship between NDVI trends and biophysical and socio-economic variables, but the findings did not yield results of statistical inference. Nkonya et al. (2011a) conducted multivariate correlation and regression analyses of the NDVI change against changes in rainfall, demography, and economic growth. However, their results did not appropriately support any causal analysis because of low determination coefficients.

Satellite images with medium resolutions (e.g., LANDSAT, SPOT) have been used to detect signals of land degradation at regional levels. Shrestha et al. (2005) used imaging spectrometer data to detect and map desert-like surface features. The grazing-induced land degradation could be identified by using vegetation cover index values derived from multi-temporal, remotely-sensed data in association with spatial models of the grazing impact on landscapes (Pickup and Chewings, 1994). Chen and Rao (2008) selected multiannual LANDSAT TM/ETM data to determine the rate and status of grassland degradation and soil salinization in northeast China. Several indicators of land degradation were used with Geographical Information System (GIS) techniques (i.e., capturing, processing, analyzing, displaying, and storing spatial data) to examine the severity of the land degradation risk in the northern part of Shaanxi province in China (Jabbar and Chen, 2006). The researchers used LANDSAT TM images at different times to interpret and use land cover change, vegetation degradation, and land degradation maps. The LANDSAT

TM/ETM data were also utilized to identify and map the susceptibility to land degradation in a catchment of Zimbabwe with the integration of agro-ecological zones, vegetation cover, and population density (Mambo and Archer, 2007). Multi-temporal, 1-km Advanced Very High Resolution Radiometer (AVHRR) NDVI time-series was used for assessing the effects of human-induced land degradation to compare degraded with non-degraded rangelands in South Africa (Wessels et al., 2004) and to identify the risk of land degradation in southern Mauritania (Thiam, 2003).

Although the vegetation-based and satellite-based approaches have strengths for the regular and quantitative assessment of changes in land productivity over large spaces and long periods, they still have certain shortcomings. While changes in the NPP may indicate geographic hotspots of land degradation, such an indicator does not necessarily equate to all soil degradation processes such as soil erosion, nutrient depletion, and salinity (Vogt et al., 2011). Long-term satellite NDVI data (e.g., AVHRR) have very coarse spatial resolutions (e.g., 8 x 8 $km^2$) that limit the accuracy of an assessment. Satellite data with higher spatial resolutions are not available over a long period.

#### 1.2.1.3 Land assessment practices in Vietnam

The area of hill and mountain land comprises 24 million ha, accounting for 73% of the total area. According to the data on the level of land degradation in the Asia-Pacific region that were collected by the FAO (Ha, 1996), the proportion of degraded land in Vietnam is top ranking, accounting for 49% of the country's total area. Since this estimation was drawn from a few field soil erosion measurements, it is not very useful for supporting land management planning and practices.

Remote-sensing technologies have mainly focused on editing topographic maps, compiling some thematic maps in land management, and some environmental aspects on a specific scale of temporal and spatial resolution. Although remote sensing has been used by some research teams to detect land use and land cover change in Vietnam (De et al., 2008; Duong, 2004; Kham et al., 2007; Müller and Zeller, 2002; Quy et al., 2001), no spatial-temporal trend analysis has been made for assessing long-term biomass productivity decline in Vietnam. So far, there has been no long-term assessment of land degradation using remote-sensing data across the country.

#### 1.2.1.4 Moving towards to a full ecosystem and human-environment system approach

*The full ecosystem perspective in land degradation assessment*

The phenomenon of land degradation involves the combination of many interrelated degradation processes (e.g., soil erosion; deterioration of physical, chemical, and biological soil properties; loss of species diversity; loss of biophysical and economic productivity; and long-term loss of natural vegetation, reduction of water availability and quality) that reduce the land's performance capacity regarding the regulation functions of accepting, storing, and recycling water, energy, and nutrients. Among various land ecosystem functions and services, biomass productivity has been recognized as an overall indicator (Bai et al., 2008b; Eswaran et al., 2001; Vlek et al., 2008).

*Multi-scale and multi-criteria perspective in land degradation assessment*

Since land degradation is a complicated phenomenon caused by the interactions between human and environment over multiple scales in time, space, and human organization (Reynolds et al., 2007), interpreting the phenomenon requires a multi-scale approach. Le et al. (2012b) highlighted several reasons for the multi-scale and multi-criteria approach to assess land degradation. The two important reasons of these are: (1) different data availability over scales, and (2) the scale-specific information needs of different stakeholder groups.

The investigation of land degradation requires the integration of a wide range of socio-economic and biophysical factors. The availabilities of social, economic and biophysical data are scale-specific. For example, accurate soil data are often available at plot and watershed scales, but lacking at national or regional scale. Socio-economic data are often available in statistic year books of districts, provinces and nations, but not always ready at farm and village scales. Because it is difficult to get all data of required social, economic and biophysical variables at a single scale, integrated land degradation assessment in practice seems to be necessarily done at different scales (Le et al., 2012b).

Multi-scale approach bears also the potential to inform scale-specific land management objectives. On national and regional scales, it will be impractical to perform intensive land degradation assessments that capture involved biophysical (e.g., soil erosion, soil nutrient leaching or mining) and social processes (e.g., individual adaptive decisions of users on land use practices). On such large scales, policy-makers and managers mainly need information on the locations of severely degraded areas to prioritize budgets and man-power for comprehensive, intensive research and mitigating interventions (Le et al., 2012b; Vogt et al., 2011). They may also need information on key land degradation causes in specific to agro-ecological (or major land use) zones to formulate more region-specific policies to combat effectively land degradation (Vlek et al., 2010; Von Braun and Gerber, 2012).

On the community-landscape scale, where land degradation is obvious and land-use decisions need to be made, the focus is no longer on the assessment of the status-quo degradation, but rather on the understanding of what constrains farmers to adopt suitable management practices (Le et al., 2012a; Le et al., 2012b). This understanding will be useful for informing the formulation and implementation of policies to leverage farmer adoption of sustainable land use practices. There were several studies on factors influencing smallholder adoption of sustainable land use practices (including nutrient management practices) (e.g., Paudel et al., 2009; Adhikari, 2011, Zhou et al., 2010; Aregay and Minjuan, 2012; Chouichom and Yamao, 2011; Marenya and Barrett, 2007) assuming a uniform causal pattern across the study community. However, this assumption may not be plausible if the target community has many household/farm types that can have different patterns of response to the affecting factors (Le, 2005; Tittonell et al., 2010; Le et al., 2012a). Thus, household/farm type needs to be taken into account for identifying factors constraining farmer adoption of sustainable land management practices (Le et al., 2012a; Miyasaka et al., 2012; Smajgl and Bohensky, 2013).

Although the multi-scale approach to land degradation assessment is a genuine need, so far, existing studies on the topic have been mostly limited to a single scale, often depending on the researcher’s disciplinary tradition. Geographers and landscape ecologists often focus on the assessment of changes in vegetation productivity on global and continental scales, and using macro-attributes of the natural (e.g., climate and soil) and human (e.g., population density, land-use type) environment to identify the causes of degradation (Bai et al., 2008b; Vlek et al., 2008; Vlek et al., 2010). Many quantitative studies on soil degradation have been carried out by soil scientists and agronomists, mostly based on field measurement on plot or farm scales (e.g., Abbasi et al., 2007; Abu, 2013).

Over the last decade, some efforts in multi-scale assessment and modeling have focused mainly on land-use change research (de Koning et al., 1999; Park et al., 2005; Veldkamp et al., 2001), but not yet to assess land degradation. Multi-scale approaches to land degradation assessment have been considered by a few of studies. Gray (1999) investigated the relationship between indicators land degradation at landscape scale (e.g., vegetation cover using aerial photos) and field/plot scale (e.g., measured soil properties). However, because the study was only carried out in small areas (i.e. three villages in southwestern Burkina Faso) it is difficult to judge whether the used approach is working for other sites. Reed et al. (2011) have recently suggested a hybrid methodological framework to incorporate multiple sources of information from local to national and international scales for land degradation monitoring and assessment. However, the hybrid framework is still at a conceptual level without demonstrative case studies. Multi-scale assessments of land degradation in Volta river basin in West Africa (Le et al., 2012) and in northern Uzbekistan (Dubovyk, 2013) quantified the trends and magnitudes of biomass productivity at the regional scale, then compared with soil erosion modeled at local scale, or signs of soil degradation observed in sampled fields. However, these studies have not yet investigated socio-economic and environmental causes of land degradation.

### 1.2.2 Knowledge gaps

The cited literature reviews show the following knowledge gaps that need to be filled in further research:

- There is a lack of a multi-level framework to guide the organization of scale-specific, land degradation assessments and integrate them to generate knowledge for supporting mitigation policies.
- Although some studies have isolated human-induced land degradation from climate-driven signals, the methods for decoupling these two factors, as well as identifying socio-ecological types of the land degradation hotspots, still need to be verified.
- Intermediate and underlying socio-ecological causes of land degradation across a socially and ecologically diverse nation such as Vietnam are still to be discovered. This is important for national policies on land management and sustainable agriculture.
- At the level of identified hotspots, it is necessary to understand what constrains farmers to adopt suitable management practices. As the constraints may be specific to different household/farm types, the analysis of these constraints may need to be done in specific to livelihood types that still need to be defined.

## 1.3 Research questions

*From a methodological framework view*

- How can a multi-scale, land degradation assessment be organized to meet scientific requirements (reliable and comprehensive) and be relevant to stakeholders' needs in mitigating land degradation?

*At the national level*

- How can human-induced degradation signals be differentiated from climate-driven ones? Where are the most striking places of land degradation deserving particular policy attention?
- What are the biophysical and socio-economic causes of land degradation in Vietnam?

*At the degradation hotspot level*

Given that adequate nutrient availability is crucial for warranting the long-term productivity of agro-ecosystems:

- Do different types of farms have different patterns of behavioral response to biophysical, economic and social drivers? If they have, what are the livelihood type-specific constraints for farmer to use of mineral fertilizers and manure, knowing that the absence of nutrient inputs ineluctably leads on the long term to soil degradation (Bo et al., 2003)?

## 1.4 Approach of the thesis

In the light of the full ecosystem perspective and human-environment interactions, a multilevel framework is formulated for the assessment of land degradation from national to farm scales. The dependent variable of assessments on all scales is land degradation, defined as the persistent reduction or loss of biological and economic productivity of the land. However, concrete dependent indicators are level relevant, based on the review of related literature. At the national level, the NPP trend (approximated by the trend of inter-annual NDVI) is used as the indicator of land degradation, since this parameter is ecologically and socially relevant on such a large scale (Bai et al., 2008b; Vlek et al., 2008; Vlek et al., 2010; Vogt et al., 2011). At the hotspot level, the indicators of land degradation are directly linked to human activities. There the mineral fertilizer use and adoption of manure are used as dependent variables. The portfolio of explanatory variables also varies along the assessment scales, which are described in corresponding chapters.

Besides the multilevel causal analyses, the socio-ecological categorization of the land environment and household farms is done to provide typological frames to (1) define typical human-environment system cases for an in-depth analysis and (2) aggregate/upscale case-specific findings to regional/national lessons for informing policies.

This work is a cumulative Ph.D. thesis, consisting of three research papers presented in Chapters 2 through 4. A graphical overview of the thesis is given in Figure 1.1. The thesis begins with an assessment of biomass productivity reduction at the national level (Chapter 2) and the socio-ecological causes/drivers of land degradation (Chapter 3). Chapter 4 presents a typology of household/farms in the hotspot district of land degradation and the type-specific social and ecological determinants of smallholders' decisions on mineral fertilizer and manure uses. Chapter

5 summarizes the findings, provides the general discussion on the entire study, and offers recommendations for future research.

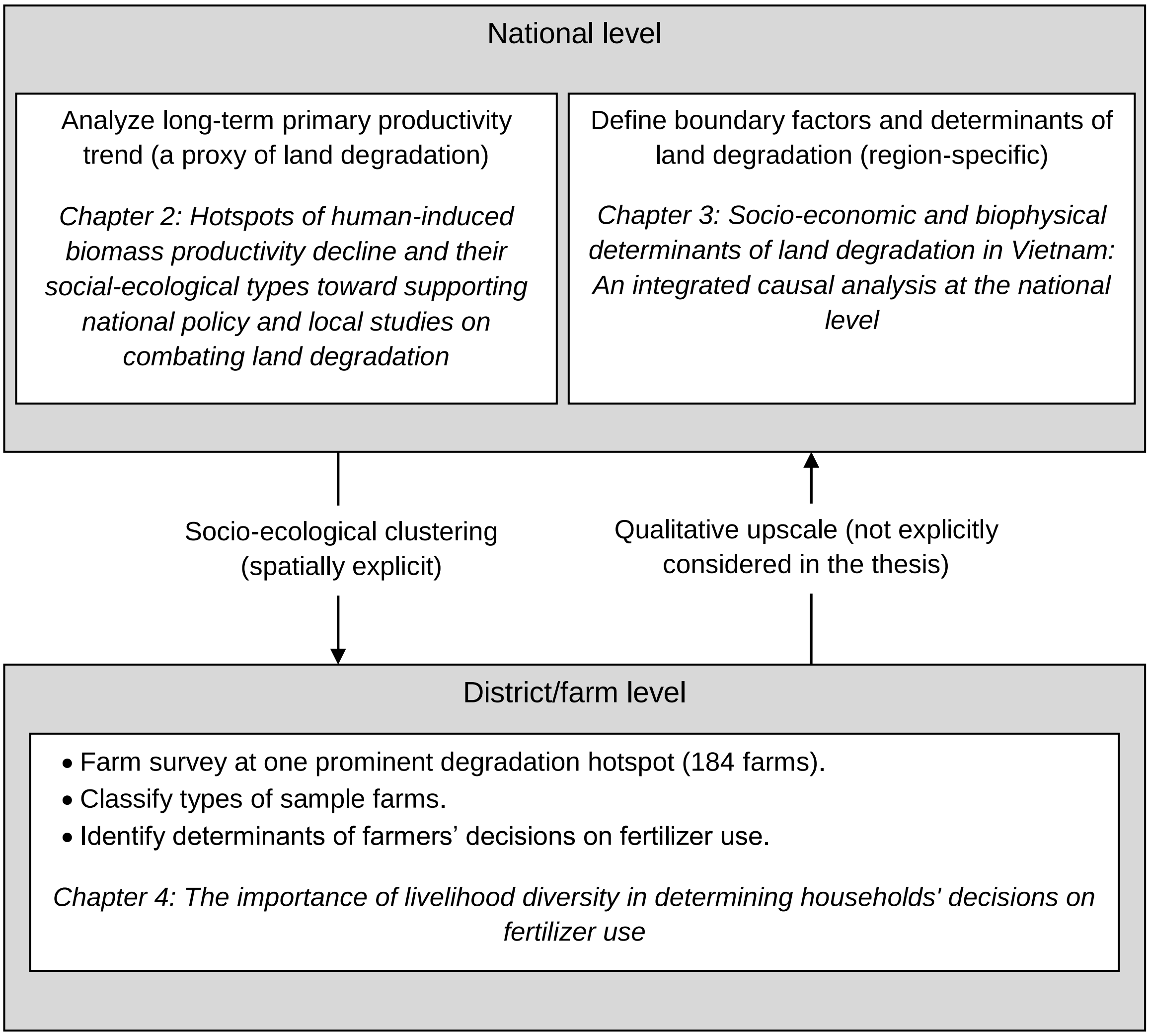


**Figure 1.1** Overview of the chapters of this thesis in multi-level assessment of land degradation

Chapter 2 delineates the geographic hotspots of human-induced land degradation in the country and classifies the socio-ecological characterizations of each specific hotspot type. The long-term (1982–2006) biomass productivity trend (approximated by NDVI) is analyzed, and this trend is used as a proxy of land degradation. The areas of human-induced productivity decline are separated from those areas driven by climate dynamics by analyzing the temporal correlation between climate factors (rainfall and temperature) and NDVI time-series over the last 25 years. The human-induced productivity decline is compared to relevant data (land use map, forest map, and the NAP data). A set of socio-ecological variables for categorizing the area clusters of human-induced, biomass productivity degradation is selected. This is followed by a discussion on the assessment of the NDVI-based, biomass productivity degradation using a multi-aspect approach; the implications for the land degradation combating policy; the limitations of the method used, and improvement strategies.

Chapter 3 identifies and characterizes the biophysical and socio-economic factors that significantly affect land degradation across Vietnam, then interprets the underlying causes. Both the spatial extent and intensity of degradation in three land-use zones (agriculture, forest, and severely degraded abandonment) are used as dependent variables for inferential statistics. Multilinear regression and binary logistic regression are used in a complementary manner to identify the economic and demographic drivers and biophysical factors. The new features of this approach are discussed, as well as the implications for national policies on combating land degradation.

Chapter 4 considers one of the most degraded hotspots found at the national level (reported in the first paper) for further research. A survey of 184 households is conducted in the Yen Chau District, Son La Province, a typical district of the uplands in Vietnam's northwest mountains in terms of the geographic location, land-use system, and socio-economic features. The diversity of smallholder farming systems in the study area is characterized by identifying the socio-ecological types of households/farms. For the household types found, the socio-ecological determinants of their decisions on mineral fertilizer and manure use are identified. The variables for analyses are based on the livelihood framework concept, which includes five principal categories of livelihood assets (i.e., physical, human, financial, natural, and social capital).

Chapter 5 synthesizes the key findings; discusses the goals, limitations, and recommendations of the thesis; draws the conclusions; and provides an outlook on future research needs.

# 2. Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation *


## Abstract

Identification and social–ecological characterization of areas that experience high levels of persistent productivity decline are essential for planning appropriate management measures. Although land degradation is mainly induced by human actions, the phenomenon is concurrently influenced by global climate changes that need to be taken into account in land degradation assessments. This study aims to delineate the geographic hotspots of human-induced land degradation in the country and classify the social–ecological characterizations of each specific degradation hotspot type. The research entailed a long-term time-series (1982–2006) of Normalized Difference Vegetation Index to specify the extents of areas with significant biomass decline or increase in Vietnam. Annual rainfall and temperature time-series were then used to separate areas of human-induced biomass productivity decline from those driven by climate dynamics. Next, spatial cluster analyses identified social–ecological types of degradation for guiding further investigations at regional and local scales. The results show that about 19% of the national land mass experienced persistent declines in biomass productivity over the last 25 years. Most of the degraded areas are found in the Southeast and Mekong River Delta (17,984 $km^2$), Northwest Mountains (14,336 $km^2$), and Central Highlands (13,504 $km^2$). We identified six and five social–ecological types of degradation hotspots in agricultural and forested zones, respectively. Constraints in soil nutrient availability and nutrient retention capability are widely spreading in all degradation hotspot types. These hotspot types are different from each other in social and ecological conditions, suggesting that region-specific strategies are needed for the formulation of land degradation combating policy.


* This chapter has been published as:
Vu, Q.M., Le, Q.B., Vlek, P.L.G., 2014. Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation. Global and Planetary Change 121, 64-77. DOI:10.1016/j.gloplacha.2014.07.007

## 2.1 Introduction

Land is understood as a terrestrial ecosystem that includes not only soil resources, but also vegetation, water, other biota, landscape setting, climate attributes, and ecological processes (MEA, 2005; Scherr and Yadav, 1996; Vlek et al., 2008) that operate within the system, ensuring its functions and services. From internationally authoritative concepts of United Nations Convention to Combat Desertification (UNCCD, 2004) and Millennium Ecosystem Assessment (MEA, 2005), *land degradation is defined as the persistent reduction or loss of land ecosystem services, notably the primary production service* (Safriel, 2007; Vogt et al., 2011). First, this definition focuses on the ecological services of the land: land degradation makes sense to our society only in the context of human benefits derived from land ecosystems uses (Safriel, 2007). Negative changes in soil component (e.g., soil erosion, deteriorations of physical, chemical, and biological soil properties) are concerned in the changes resulting in reductions of supporting (e.g., primary production), provisioning (e.g., biological products including foods) and regulating (e.g., carbon sequestration) services of the land. In addition, the definition emphasizes the pivotal role of primary production among a wide range of land ecosystem services. The crucial reason for this emphasis is that primary production generates products of biological origin, in which much of other ecosystem services depend on (Safriel, 2007). Primary production is the basis of food productions, regulates water, energy, and nutrient flows in land ecosystems, sequestrates carbon dioxide from the atmosphere and generally provides habitats for diverse lives (MEA, 2005).

From the view of above-mentioned definition of land degradation, the phenomenon can involve not only soil degradation, but also the degradation of vegetation functions and services either within a land-use/cover type (e.g., forest degradation and yield-degraded crop land), or a conversion of natural productive land cover type to a less productive one (e.g. deforestation). In fact, soil and vegetation degradations have close inter-linkages as they are the two pivotal components of land ecosystems (Safriel, 2007; MEA, 2005).

Land degradation has been considered as a major global environmental issue. Eswaran et al. (2001) estimated that about 13.6 million km$^2$ of global land are moderately or severely degraded. In the tropical countries, where livelihoods are usually agriculture-based, land degradation is a serious problem for food security and development of society (FAO, 2010; Vlek et al., 2010).

Vietnam is one of typically national case of land degradation as precedent reports have shown profound figures of the phenomena. About 93,000 km$^2$ of land (28% of the national land mass) was affected by desertification, of which 20,000 km$^2$ is seriously degraded (UNCCD, 2006). Land degradation in Vietnam is driven by both natural and anthropogenic phenomena (Cooke and Toda, 2008). The land has gradually lost its biological productivity due to soil erosion, landslide, lateralization, and acidification. In addition the fast development of economy, modernization–urbanization, and high growth in population have created a high pressure on land for agricultural production (Müller and Zeller, 2002). Those factors act as drivers of land-use change (e.g., deforestation, forest degradation, and shortening of fallow periods in shifting cultivation in the uplands; and more intensified agriculture in the lowlands) that can have a direct impact on soil's and land ecosystem's functions and services, including the biomass productivity of the land. To combat land degradation on the national level, policy makers often need information about areas of severe degradation in order to prioritize national budgets and plan strategic interventions (Le et al., 2012b; Vogt et al., 2011). First, the main requirement at this *large scale* is a view of areas *where* degradation magnitude and extent are relatively high, i.e., *geographic degradation hotspot*, for prioritizing the investments on the restoration or reclamation of degraded land, and focal field-based studies. With the geographic hotspot approach, the expected output is the map of degradation hotspots that can be seen as the first version of land degradation map to guide the obtaining of the more comprehensive and accurate one in the next steps. Although the National Action Programme to Combat Desertification for the Period 2006–2010 and Orientation to 2020 has recently prioritized four regions that urgently need anti-degradation measures (i.e. the Northwest, the Central Coast, the Central Highlands and the Mekong River Delta) (NAP, 2006), the report was based on national experts' opinions and did not show explicitly the areas for policy interventions. Second, efforts to mitigate land degradation at the social level also require identification of the *potential causes* of degradation in different regions, which are important for formulating cause-targeted management strategies.

Large-scale land degradation assessments based directly on the temporal states of soil parameters is constrained by the lack of soil data for long-term quantitative comparisons (Safriel, 2007). With current technologies, it would be very costly to track the dynamics of soil properties directly over longer time spans at a national or regional scale to develop time-series of soil properties that could detect *persistent changes* in soil status (compared to a baseline). On a continental or national scale, these long-term comparisons are basically impossible (Vlek et al. 2008, 2010). Early global land degradation assessments evaluated soil parameters, and were based on qualitative, subjective assessments by experts (Oldeman et al., 1991).

As an alternative, recent large-scale land degradation assessments have been based on quantitative evaluation of changes in vegetation greenness or net primary productivity (NPP), which has been explicitly postulated in the UNCCD's definition. This approach has become feasible with the availability of satellite-driven time-series of vegetation data spanning the past three decades and covering the whole globe. The Normalized Difference Vegetation Index (NDVI), a relative measure of vegetation health and photosynthetic process, is increasingly used for evaluating vegetation productivity decline or improvement. The relationship between the NDVI and vegetation productivity is well-established theoretically and empirically (Pettorelli et al., 2005). Previous studies (Fensholt et al., 2012; Zhao and Running, 2010) have found that NDVI is strongly correlated with NPP and is often used to estimate NPP at global, national and regional scales, and served as an indicator of NPP to monitor temporal changes in vegetation. The parameter is suitable for geographic hotspot assessment for prioritizing resource allocation in either land management policies or more detailed studies at finer scale (Vogt et al., 2011). Above-ground net primary production (represented by NDVI) has been shown to increase with increasing annual precipitation (Huxman et al., 2004), and indeed, correlation studies between climate factors (rainfall and temperature) and NDVI have been used to distinguish between human-induced and climate-induced biomass productivity decline, where any NDVI trends not explained by rainfall and temperature dynamics are ascribed to human actions (Herrmann et al., 2005; Le et al., 2012b; Li et al., 2012; Vlek et al., 2010; Wessels et al., 2007). The Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) satellite is a unique instrument that enables the assessment of global or regional vegetation dynamics over a long duration (i.e., more than two decades), which can be combined with other time-series (e.g., climate, soil, land use, and population) to allow spatially explicit interpretation of the causes and processes of degradation.

Recent reviews suggest that NDVI-based methods for detecting land degradation need to be continuously verified in different geographic regions (Vogt et al. 2011). Thus far, in Vietnam, spatio-temporal trend analysis has not been used for assessing long-term changes in biomass productivity of the land on a national scale. Further, the causes of degradation have not been systematically identified on a national scale and in a spatially explicit manner.

This study aims to (i) delineate the geographic hotspots of human-induced biomass productivity decline in Vietnam over the last two decades, and (ii) identify different types of hotspots with respect to different social and ecological causes of biomass productivity degradation. The findings may provide a nationwide pattern that could guide follow-up studies conducted on finer scales in terms of what focus to adopt.

## 2.2 Methods and data sources

### 2.2.1 Study area

Vietnam is characterized by a complex physical geography, with three-quarters of the land territory dominated by hills and mountains. The total land area of Vietnam is about 331,051 km$^2$, of which agricultural and forest land comprises 251,273 km$^2$ (75.9% of the total area). The area used for residential, industrial and transportation purposes is 34,692 km$^2$ (10.5% of the total), and the remaining area (45,086 km$^2$ or 13.6% of the total) is bare and unused (i.e. unused flat land, unused mountainous land and rocky mountain). The land area for agricultural production is about 96,000 km$^2$ (29% of the total) (GSO 2010). The national population in 2009 was about 86 million, an increase of 26 million compared to 1985 (about 60 million) (GSO, 2010). The rapid population growth has created a high degree of pressure on land for food production as well as forest cover for nature services. From 1930 to 2000, the farming area per person was dramatically reduced from 2548 m$^2$ to 675 m$^2$ (Bo et al., 2003b). The national forest coverage decreased from 43% in 1943 (mainly multistory and dense tropical forests) to 28% in 1990 (De Koninck, 1999), then rose up to 37% by massive reforestation programs (UNCCD 2006). Today, most replanted forests are mono-species stands with rapidly growing species and simple structure.

### 2.2.2 Proxy of long-term biomass productivity decline at the national level

Given the large scale (large spatial coverage and large pixel size) and long-term perspectives of our assessment, we used the *long-term trend of inter-annual mean NDVI*, driven from AVHRR satellite images, over the period 1982–2006, as a proxy for persistent decline or improvement in NPP of the land, thereby reflecting past land degradation. The approach has been used by many studies (Bai et al., 2008b; Helldén and Tottrup, 2008; Herrmann et al., 2005; Le et al., 2012b; Vlek et al., 2010). The functional relationship of vegetation productivity to soil productivity and land services can be found in Safriel (2007). The NDVI time-series data were downloaded from Global Inventory Modeling and Mapping Studies (GIMMS), published by the Global Land Cover Facility (GLCF) (http://glcf.umd.edu/data/gimms/ — Data assessed on 30 May 2014). The NDVI dataset was calibrated and corrected for view geometry, volcanic aerosols, and other effects not related to vegetation change (Pinzon et al., 2005; Tucker et al., 2005). As a result, this new GIMMS NDVI dataset, used in this study, is relatively consistent over time and is of higher quality compared to the previous versions produced by the GIMMS group (Brown et al., 2003). Using Terra MODIS

NDVI as a reference, Fensholt et al. (2009) found that the GIMMS NDVI dataset is well-suited for long term vegetation studies of the Sahel–Sudanian areas. To this end, we aggregated the original GIMMS NDVI time-series (8-km pixel size, bi-weekly, period 1982–2006) (Pinzon et al., 2005; Tucker et al., 2005) to get the time-series of annual mean values as 12-month averages for inter-annual NDVI trend analysis.

In a comprehensive review of using the satellite-derived NDVI to assess biomass productivity, Pettorelli et al. (2005) identified pitfalls to avoid in the use of this indicative method. Their advices include cautions with confounding effects on the NDVI–vegetation productivity relationship: (1) remnant cloud-cover effects in humid tropics; (2) seasonal variations in vegetation phenology (in proportional with weather seasonality) and time-series autocorrelation; (3) site-specific effects of vegetation structure and site conditions (e.g. topography and altitude). We considered these caveats in our interpretation of inter-annual NDVI trends to avoid the above-mentioned pitfalls, as justified in the following:

- To partly avoid the effect of cloud cover or cloud shade, only non-flagged GIMMS pixels (i.e., flag = 0 indicates a good value of NDVI; Tucker et al. 2005) were considered.
- To minimize the confounding effects of seasonal variations and time-series autocorrelation, we used annual average NDVI and focused on the declining "hotspots" where the inter-annual NDVI trend is most remarkable (i.e., with a statistical significance and the absolute trend magnitude greater than 10% of the beginning year over 25 years (Vlek et al. 2010; Le et al. 2012b). This treatment is supported by the recent findings of de Jong et al. (2011). They found that inconsistencies between the linear trends of annually aggregated GIMMS NDVI and the seasonality-corrected, non-parametric trends of the original GIMMS NDVI time-series (biweekly) were mainly on areas with weak or non-significant NDVI trends, which are not central in our hotspot approach.
- The NDVI–vegetation productivity relationship can be saturated, thus biased in areas with dense canopies (Pettorelli et al. 2005). Dense vegetation with Leaf Area Index (LAI) more than 4, the relationship between NDVI and the vegetation biomass tend to be saturated (i.e., NDVI is less sensitive to actual biomass change), thus should be used with caution (Carlson and Ripley, 1997). Whereas for LAI > 6, NDVI is not sensitive to near infrared (NIR) signal (Asrar et al., 1984; Pettorelli et al., 2005), and thus should not be used. We used the LAI dataset provided by Xiao et al. (2013) to calculate the average of the annual mean LAI in years 1985, 1990, 1995 and 2000 for delineating pixels with this saturated NDVI–biomass relationship.
- Given a pixel and the long-term period considered (25 years), changes in plant species or life-form composition (often associated with either natural vegetation successions or land use changes) may weaken the positive correlation between inter-annual NDVI and NPP (e.g., Mbow et al. 2013). As there has been no available data of this type of vegetation change over Vietnam, we are aware about the potential problem in our interpretation and discussion of the results.
- As NDVI–vegetation productivity can be conceptually different between different vegetation or land cover/use types, we interpreted the results for each spatial stratum of land use and other ecological, socio-economic factors to gain more insights about likely degradation processes and affecting factors in the delineated hotspots, as recently suggested by Sommer et al.

(2011), Vlek et al. (2010), and Le et al. (2012). At the resolution of this national study (i.e., 8-km pixel) and the patchy land-use patterns in Vietnam, many sub-classes of scattered land cover/use (e.g. slash-and-burn field, mountain paddy rice terraces and fruit plantations) disappear. Thus, we use three broad types as shown in Table S2.1 for interpreting the meaning of the calculated NDVI trends

### 2.2.3 Pixel-based temporal trend of biomass productivity

For each pixel *i*, the long-term trend of annual NPP (via vegetation index) can be formalized by the slope coefficient ($A_i$) in the simple linear regression relationship

$$V_i = A_i \times t + B_i \qquad (1)$$

where $V_i$ = annual mean NDVI, $A_i$ = long-term trend of NDVI, $t$ = year (elapsing from 1982 to 2006), and $B_i$ = intercept (an indicator for a possible delay in the onset of degradation). The computed slope coefficient $A$ for each pixel was tested for statistical significance at the confidence levels of 90% ($P < 0.1$), which is sufficient for long-term trend analyses of noisy parameters like NDVI (Le et al., 2012b; Vlek et al., 2010).

### 2.2.4 Validating whether inter-annual NDVI decline can indicate NPP decline

To check whether the temporal trend of inter-annual GIMMS NDVI can be credibly used as a proxy of temporal NPP trend, we compared the spatial pattern of GIMMS NDVI trend with the pattern of NPP trend driven from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite time-series for the overlap period between the two datasets (i.e., 2000–2006). The temporal NPP trend was computed based on the MOD17 NPP dataset with the spatial resolution at 1 km (Zhao and Running, 2010). The algorithm for calculating MOD17 NPP is based not only on the MODIS-driven vegetation indices, Fraction of Photosynthetically Active Radiation (FPAR) and Leaf Area Index (LAI), but also meteorological data from independent sources. These weather data include daily minimum temperature, daytime temperature, daily average temperature, daily vapor pressure, and daily total downward shortwave solar radiation. The MOD17 NPP data were well validated against ground measured NPP data (Zhao and Running, 2010, 2011).

We re-sampled the MOD17 NPP data from 1 km to 8 km resolution, using the nearest neighborhood algorithm in ArcView GIS 3.2 software to match to the resolution of the GIMMS NDVI dataset, and then performed the following two evaluation tests:

- Evaluation of the overlap area between the GIMMS NDVI and MOD17 trends across the country.
- Calculation of temporal correlation between inter-annual mean GIMMS NDVI and MOD17 NPP for each degraded pixel over the test period (2000–2006).

We also qualitatively compared the overall NDVI trends in each agro-ecological region with recorded knowledge about deforestation/reforestation and agricultural intensification during the past 30 years.

### 2.2.5 Isolation of human-induced degradation from climate-driven impact

The significantly negative long-term trend of NDVI (coefficient $A$ in Equation (1)) can be attributed to either climate change (e.g., inter-annual variation in rainfall and temperature) or human activities (e.g., land cover/use conversion and/or change in land use intensity). The correlation between inter-annual NDVI and climate factors (rainfall and temperature) can be used for distinguishing human-induced land degradation from climate-driven phenomena (Vlek et al., 2008, 2010). Hence, this study used annual rainfall and temperature data for the period 1982–2006, which was extracted from the TS 3.0 dataset of the Climatic Research Unit (CRU) at the University of East Anglia (UK). The original data include grids of monthly rainfall and temperature data at a spatial resolution of 0.5°, covering the 1901–2006 period (Mitchell and Jones, 2005). To match the spatial resolution of AVHRR-NDVI data for later analysis, the grid cells of rainfall and temperature data were downscaled from 0.5° to 8 km resolution, using nearest neighbor statistics. Urban areas (cities and industrial zones) were excluded from the analysis.

To isolate human-induced from climate-driven biomass production decline, we applied two methods: the trend-correlation stepwise method (Le et al. 2012b; Vlek et al. 2010) (hereafter referred to as *Trend-Correlation* method) and residual trend analysis method (Evans and Geerken, 2004; Herrmann et al., 2005; Li et al., 2012; Wessels et al., 2007) (hereafter referred to as *ResTrend* method).

*Trend-Correlation method:* First, for each pixel, Pearson's correlation coefficient ($R_i$) and determination coefficient ($R_i^2$) between inter-annual NDVI and climate factors (rainfall and temperature) over the 1982–2006 period were calculated. We tested the statistical significance for pixel-based correlation and determination coefficients at a confidence level of 95% ($p <0.05$). A pixel was considered to have a strong correlation between its inter-annual NDVI and climate factors (rainfall and temperature) if the $R_i^2$coefficient was significant ($p$ < 0.05) and greater than 0.5, together with positive $R_i$. If the pixel had a significantly negative NDVI trend (negative $A_i$, $p$ < 0.1) and a strongly positive vegetation–climate correlation ($R_i^2$> 0.5; $R_i$ > 0; $p$ < 0.05), we concluded that the NDVI decline at the location was mainly determined by the climate factors. Otherwise, the NDVI decline was mainly caused by human activities.

*ResTrend method*: For each pixel $i$, the relationship between NDVI and climate factors (rainfall and temperature) was estimated using linear regression analysis:

$$V_i = A_{i\_p} \times P + B_{i\_p} \quad (2)$$

where $V_i$ = NDVI, $A_{i\_p}$ = the slope coefficient, $P$ = annual precipitation, and $B_{i\_p}$ = intercept. Based on Equation (2), we calculated the predicted value of inter-annual NDVI ($V_{i\_pred}$) for each pixel from the observed precipitation values ($P$). The NDVI residual ($RES_i$), i.e., the difference between observed NDVI ($V_{i\_obs}$) and predicted NDVI ($V_{i\_pred}$) ($RES_i = V_{i\_pred} – V_{i\_obs}$), was then calculated for each pixel $i$. Next, the temporal trend of the NDVI residuals for each pixel was calculated on the time-series of NDVI residuals by the linear regression equation:

$$RES_i = A_{i\_res} \times t + B_{i\_res} \quad (3)$$

where $RES_i$ = NDVI residual, $A_{i\_res}$ = NDVI residual trend, and $B_{i\_res}$ = constant. The trend of NDVI residuals over 25 years is the clue for isolating human-induced land degradation from climate-driven impacts. If there is a significant temporal trend of $RES_i$, then the declining biomass production would additionally be derived by other hidden factors (i.e., human activities) besides the climate variable. Otherwise (the inter-annual NDVI residues are free to any temporal trend), the declining biomass production would be caused by only the climate factor considered in Equation (2).

We compared the spatial patterns of the human-induced land degradation areas delineated by both methods. As each method may be able to detect some degraded areas that may not successfully be detected by the other, the total merging of degraded areas by both methods should be considered. Moreover, from the validation perspective, the confidence for the degraded areas shared by two different methods should be higher than that identified by only one method (i.e., convergent validity as described by Scholz and Tieje (2002)).

### 2.2.6 Socio-ecological classification of degradation hotspots

We used K-Mean Cluster Analysis (K-CA) for identifying the locations of different types of degradation hotspots associated with different profiles of social and ecological factors of degradation. K-CA is a simple and popular method to find representative classes or homogeneous groups within raw datasets (Bradley and Fayyad, 1998; Robinson et al., 2006). Like other spatial analysis studies, K-CA was chosen because we had a large number of cases (N = 978 degraded pixels) that caused difficulties to interpret grouping results using hierarchical cluster analysis. Moreover, unlike hierarchical methods, using K-CA helps (1) avoid problems of chaining and artificial boundaries and (2) work on the original input data rather than on a similarity matrix (Kintigh and Ammermann, 1982).

Based on reviewing the literature regarding common determinants of land degradation (Jorgenson, 2006; Jorgenson and Burns, 2007; Jorgenson et al., 2011; Jorgenson and Kuykendall, 2008) and data availability at the national scale, we selected eleven variables for entrancing the K-CA (see Table 2.1). The variable set covered four main categories: (1) natural constraints (slope and soil combined constraints), (2) physical and institutional accessibilities (distances to main road and district capital, forest protection), (3) human demography (population density, share of urban population, and population density change), and (4) economic development status (mean gross domestic product per capita, gross domestic product growth, and poverty index).

Surface slope (SLOPE) is widely recognized as one of the natural factors for soil erosion (De et al., 2008; Wezel et al., 2002b). The variable of combined soil constraints (SOIL-CONSTRAINTS) is an ordinary index that combines different specific soil constraints[2] for vegetation growth and crop production, namely: nutrient availability, nutrient retention capability, root condition, oxygen availability to root, excess salts, toxicity and workability. The combined soil constraint was extracted from the spatial dataset of the Global Agro-Ecological Zones Assessment for Agriculture (GAEZ), version 2002 (Fischer et al., 2002). The specific soil constraint data were taken from GAEZ version 2008 (Fischer et al., 2008).

[2] The combined soil constraint was used for K-CA to avoid unnecessary complication in the classifiers list. However, the identified degradation categories were then characterized regarding the specific soil constraints.

**Table 2.1** Variables used for K-CA (n = number of degraded pixels)

| *Variable* | *Definition* | *Spatial distribution* | *Source* |
|---|---|---|---|
| SLOPE | Surface slope (degree) | Pixel explicit | Calculated from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) (http://glcf.umiacs.umd.edu/) |
| SOIL-CONSTRAINT | Soil combined quality constraint (1 = no/slight, 2 = moderate, 3 = severe/very severe) | Pixel explicit | Extracted from FAO-IIASA Global Agro-ecological Assessment for Agriculture (GAEZ 2002) dataset (Fischer et al., 2002) |
| PROTECTION | Forest protection (0 = with no protection, 1 =with protection) | Pixel explicit | Extracted from National Land Use Map 2005, Ministry of Natural Resource and Environment |
| DIST-ROAD | Distance to main road (km) | Pixel explicit | Calculated from National Base Map 1999, Ministry of Science, Technology and Environment |
| DIST-TOWN | Distance to district capital (km) | Pixel explicit | Calculated from National Base Map 1999, Ministry of Science, Technology and Environment |
| POP-DENSITY | Population density (persons/km$^2$) | Province explicit | Vietnam Statistical Year Books 1995–2006, General Statistical Office (VSYB 1995–2006) |
| URBAN-POP | Urban population / total population | Province explicit | Calculated from VSYB 1995–2006 |
| POPDEN-CHANGE | Change in population density over the period 1995-2006 (persons/km$^2$) | Province explicit | Calculated from VSYB 1995–2006 |
| GDP-CAPITA | Mean GDP per capita over the period 1995-2006 (mil. VND/person) | Province explicit | Calculated from VSYB 1995–2006 |
| GDP-GROWTH | Mean growth rate of annual GDP during 1995-2006 (%) | Province explicit | Calculated from VSYB 1995–2006 |
| POVERTY | Poverty index = proportion of population that is below the poverty line | Commune explicit | National Population and Housing Census 1999, General Statistical Office (Minot et al., 2006a) |

Physical accessibility to land, such as proximities to road (DIST-ROAD) and towns (DIST-TOWN), reflects transportation costs and farmers' access to markets for buying farming inputs (e.g., fertilizer) and selling harvest products. These are important conditions for triggering agricultural expansion and intensification (Angelsen, 1996; Fox et al., 1994; Geist and Lambin, 2002; Geist and Lambin, 2004; Kaimowitz and Angelsen, 1998) which eventually affect soil fertility. Governance approaches, such as regulating access to forested land in the form of forest protection laws (PROTECTION), demonstrably prevent forests from clear cutting or selected logging activities, thereby supporting vegetation growth (Kaimowitz and Angelsen, 1998).

Population density (POP_DENSITY), ratio of urban population and total population (URBAN_POP), and change in population density (POPDEN_CHANGE) are the variables that account for population structure and dynamics. These variables are often recognized as the underlying causes of land-use changes and consequent land degradation in developing countries (Angelsen, 1996; DeFries et al., 2010; Geist and Lambin, 2002; Geist and Lambin, 2004; Jorgenson, 2006; Jorgenson and Burns, 2007). Poverty (POVERTY) heavily impedes the famers' ability to control land degradation (Barbier, 1997). Mean provincial GDP per capita over the period 1995-2006 (GDP-CAPITA) and mean growth rate of annual provincial GDP during 1995-2006 (GDP-GROWTH) are those indices of economic development which often have a strong relationship to deforestation in developing countries (DeFries et al., 2010; Jorgenson and Burns, 2007). Data for these variables were re-sampled to the same spatial resolution as the GIMMS NDVI dataset (8 km), using the nearest neighborhood algorithm in ArcView GIS 3.2.

K-CA was used to identify spatially distinct clusters of degraded pixels in three different land use zones: agricultural land, forest land, and severely degraded land. To determine the number of clusters, we used the procedure described in Robinson et al. (2006). The optimal cluster number is defined as minimal cluster number with the highest cluster homogeneity. First, for each main land use zone we ran K-CA with the number of clusters set to all values between 2 and 10. For each K-CA (with a concrete *k* value), we calculated the mean distance of cases to their assigned cluster centers. These mean distance values were then plotted along the increasing cluster number (*k* = 1, 2, …, 10). The optimal cluster number was chosen by examining the “knee” zone of the curve – the point from which the overall cluster quality (i.e., the reduction of the mean distance from cases to their cluster centers, or the overall cluster homogeneity) (Rakhlin and Caponnetto, 2006) − is not efficiently improved, even when *k* increases. We characterized the identified clusters using descriptive statistics and applied ANOVA to confirm differences among their variables.

## 2.3 Results

### 2.3.1 Areas of vegetation productivity decline and validation

Figure 2.1 depicts the trend in long-term vegetation productivity (1982–2006) in Vietnam over 25 years ($p$ <0.1). The annual relative NDVI for the 1982–2006 period was calculated by comparing long-term trends of green biomass change for the entire period to the initial status (1982) at each pixel. The areas of significant improvements in biomass productivity comprise about 23% (77,184 km$^2$) of total national land, and they were mainly found in the Red River Delta, Northeast, North Central Coast, and Mekong River Delta. About 19% (63,872 km$^2$) of national land has experienced persistent biomass decline over the last 25 years, mainly in the mangrove zones of the Mekong River Delta and the Northwestern mountains.

Evaluation tests indicated a good consistency between the temporal dynamics of GIMMS NDVI and MOD17 NPP. Within the 2000–2006 period, about 60% of the land area with NDVI decline (63,872 km$^2$) also experienced a decline in MOD17 NPP. About 75% of the NDVI declining area showed a positive correlation between inter-annual mean GIMMS NDVIs and MOD17 NPPs.

Comparisons between the spatial patterns of temporal NDVI trend with regional figures of deforest/forest degradation and agricultural intensification also show good matches. The major areas of significant improvement in annual mean NDVI, which are mainly found in the Red River Delta, Northeast, North Central Coast, and Mekong River Delta, agree with the fact that the intensification of rice-based agriculture in these areas have increased considerably since the beginning of the Era of Renovation (*Doi Moi*) in Vietnam (1986) (Linh, 2012; Thanh and Singh, 2006). Scattered pixels of improving NDVI in the Northern Mountains and hills are located mainly in protected areas or replanted forests on the National Land Use Map 2005 (MoNRE, 2005). The NDVI declines found in the Mekong River Delta are consistent with the rampant conversion of mangrove forest and swamp vegetation with rice paddies and/or aquaculture farms in the 1990s, while the NDVI declines in the Northwest and Central Highland regions could be attributed to deforestation caused by the expansion of agriculture on plateaus, hill slopes, and mountains (De Koninck, 1999; NAP, 2006; Phien and Siem, 1998; Siem and Phien, 1999). These findings were generally comparable to the four priority regions mentioned in the National Action Programme to Combat Desertification for the Period 2006–2010 and orientation to 2020 (NAP, 2006).

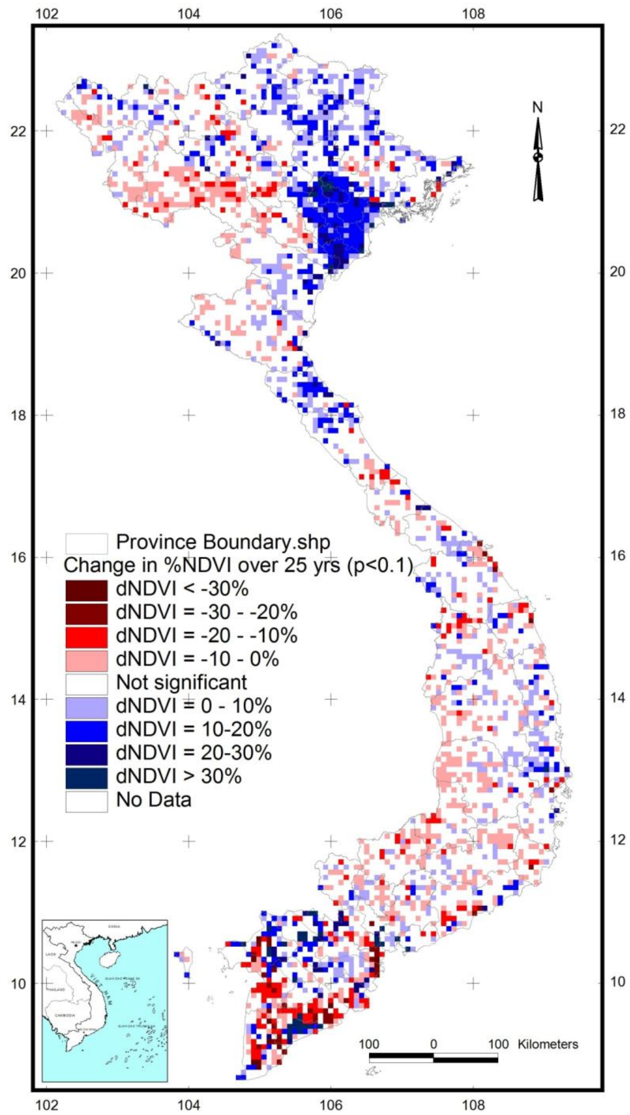


**Figure 2.1** The relative change in inter-annual NDVI over the period 1982–2006. Note: dNDVI is ratio between cumulative change in annual mean NDVI during the period and the mean NDVI in the initial year (1982). Only pixels with a statistically significant trend (p < 0.1) are shown in color

### 2.3.2 Hotspot of human-induced biomass productivity decline

The spatial pattern of the temporal correlation between annual mean NDVI and climate factors is shown in Figure 2.2a (NDVI–rainfall) and Figure S1 (NDVI–temperature). The comparison between the two maps indicates that almost all degraded areas across the country have not been associated significantly with inter-annual variations in rainfall or temperature, suggesting that land degradation in Vietnam over the last 25 years was mainly caused by non-climate factors.

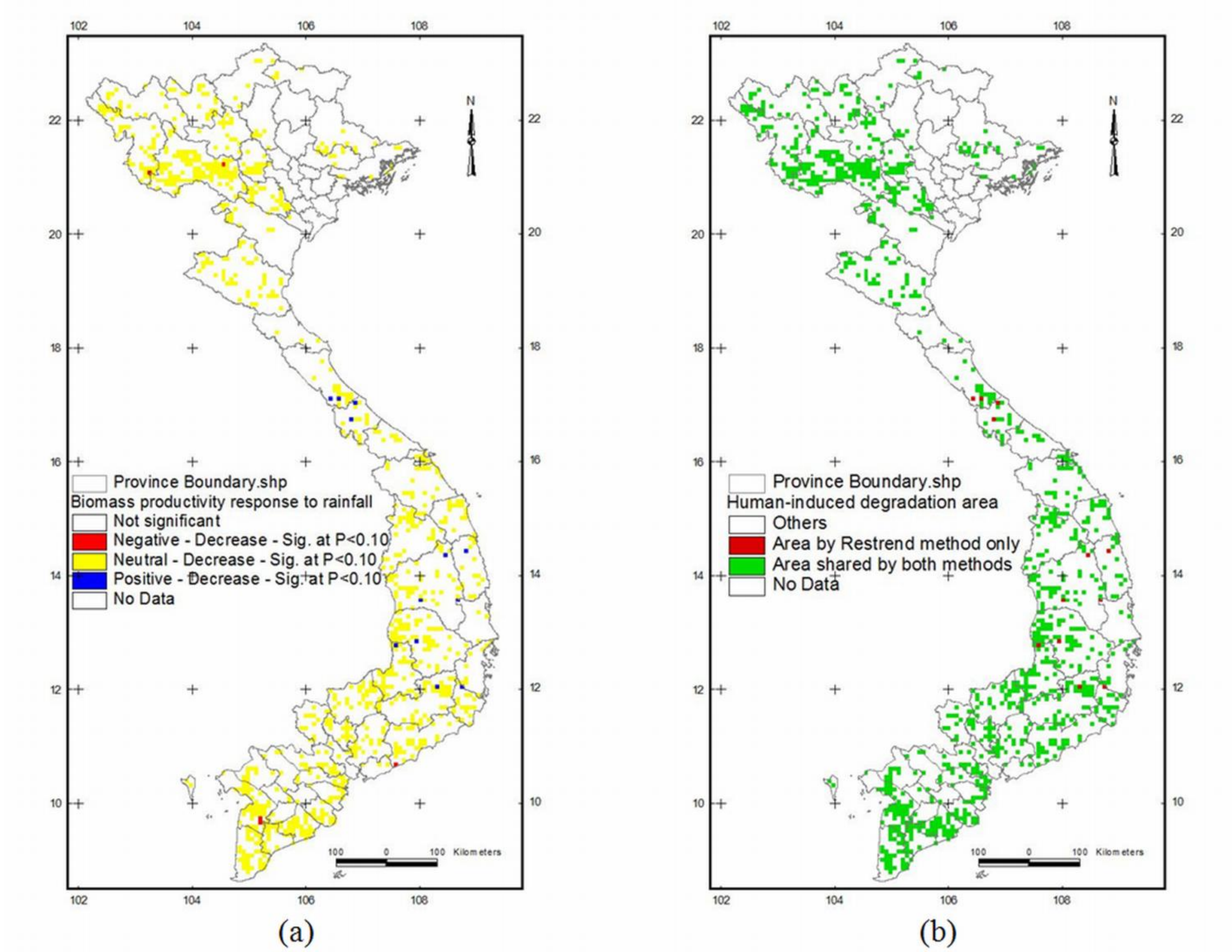


**Figure 2.2** (a) Temporal NDVI–rain correlation in the area of NDVI decline, (b) Comparison of human-induced degradation areas identified by Trend-Correlation and ResTrend methods

Using the *Trend-Correlation* and *ResTrend* methods, we identified degraded regions where climate has had a dominant impact on vegetation productivity, thereby isolating areas of human-induced biomass productivity degradation. A comparison of the results obtained using the two methods is shown in Figure 2.2b. The *Trend-Correlation* and *ResTrend* methods result in 966 and 978 pixels with human-induced biomass productivity decline, respectively. The degraded area shared by both methods is of 966 pixels (i.e. 61,824 km$^2$ or 99% of the total degraded area). The high share between the results of the two methods indicates a high confidence level for the used methodology. About 19% of the national land (62,592 km$^2$) has been degraded because of anthropogenic factors. Regions with highly degraded areas include the Northwest, Southeast and

Mekong River Delta, Central Highlands, and Central Coast (Table 2.2). The most extensive degradation hotspot has been observed in the Son La province, in the Northwest region.

**Table 2.2** Distribution of human-induced degradation area over Vietnam's sub-climate zone

| *Sub-climate zone* [a] | *Area ($km^2$)* | *% of the national area* |
|---|---:|---:|
| Northeast and Red River Delta | 3712 | 1.1 |
| Northwest | 14,336 | 4.3 |
| North Central Coast | 6592 | 2.0 |
| South Central Coast | 7680 | 2.3 |
| Central Highlands | 13,504 | 4.1 |
| Southeast and Mekong River Delta | 17,984 | 5.4 |

[a] The sub-climatic regions were proposed by Thao (2001)

### 2.3.3 Social–ecological types of degradation hotspots

Because the set of key variables that differentiates degradation hotspot types may vary over main land-use zones, the hotspot classifications were performed for degraded pixels in each broad land-use zones, i.e., agricultural land, forest land, and severely degraded land.

*Types of degradation hotspots in agricultural land*

There were 338 degraded pixels (21,632 $km^2$, or 35% of the total degraded land) found in the agricultural zone (Figure 2.4a). Overlaying this degraded agricultural area with the pattern of soil constraints taken from the GAEZ 2008 database (Fischer et al. 2008), it was found that about 69–75% of the area has moderate or high severities of soil nutrient availability and retention capability (see Table 2.3). The degraded area has also suffered soil constraints in oxygen availability to root (48% of the degraded area), workability for agricultural production (34%), and root condition (25%) (Table 2.3).

Cluster analysis of the degraded pixels in the agricultural zone, using selected social and ecological variables, identified six socio-ecological hotspot types. The socio-ecological characterization of each specific agricultural degradation hotspot types are shown in Figure 2.3 and Table S2.4, and their spatial distributions are shown in Figure 2.4a.

**Table 2.3** Area distribution (km$^2$) of different soil constraints over three main land use types. Note: Number in parentheses indicates the percentage of the degraded agricultural area

| *Detailed soil constraint* | *Severity class of degraded agricultural land* | | | *Severity class of degraded forest land* | | | *Severity class of severely degraded land* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *No/slight* | *Moderate* | *Severe/ Very severe* | *No/slight* | *Moderate* | *Severe/ Very severe* | *No/slight* | *Moderate* | *Severe/ Very severe* |
| Nutrient availability [a] | 5,376 (25) | 11,136 (51) | 5,248 (24) | 1,408 (06) | 11,776 (47) | 11,776 (47) | 3,392 (21) | 7,424 (46) | 5,312 (33) |
| Nutrient retention capability [a] | 6,848 (31) | 14,720 (68) | 128 (01) | 2,112 (08) | 22,848 (92) | – | 3,776 (24) | 12,160 (75) | 192 (1) |
| Root condition [a] | 16,192 (75) | 2,176 (10) | 3,328 (15) | 8,512 (34) | 5,440 (22) | 11,008 (44) | 8,384 (52) | 2,304 (14) | 5,440 (34) |
| Oxygen availability to root [a] | 13,440 (62) | 3,328 (15) | 4,928 (23) | 23,488 (94) | 768 (3) | 704 (3) | 11,968 (74) | 1,472 (9) | 2,688 (17) |
| Excess salts [a] | 20,672 (95) | 960 (05) | 64 (0) | 24,704 (99) | 256 (01) | – | 14,720 (91) | 960 (6) | 448 (3) |
| Toxicity [a] | 21,696 (100) | – | – | 24,960 (100) | – | – | 16,128 (100) | – | – |
| Workability[a] | 14,400 (66) | 5,184 (24) | 2,112 (10) | 7,744 (31) | 15,872 (64) | 1,344 (5) | 8,576 (53) | 6,912 (43) | 640 (4) |
| Terrain[b] | 20,160 (93) | 1,344 (06) | 256 (1) | 16,064 (64) | 6,528 (26) | 2,368 (10) | 11,008 (68) | 3,584 (22) | 1,536 (10) |

[a] Spatial data of specific soil constraints were extracted from the GAEZ 2008 database (Fischer et al., 2008)

[b] Severity classes of terrain constraint were defined based on surface slope: No/slight: 0-15°. Moderate: 15-25°, Severe/Very severe: > 25

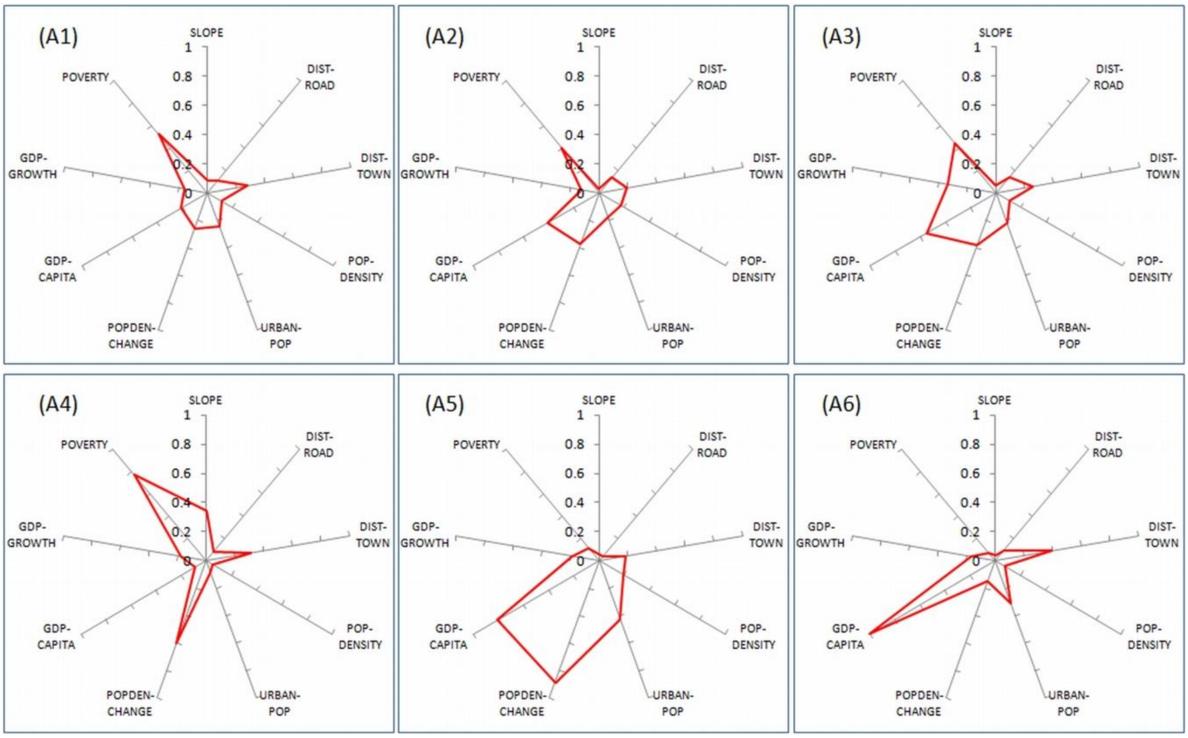


**Figure 2.3** Spider diagrams showing main socio and ecological variables of six degradation hotspot types in agricultural land. Notes: The figure shows only variables with at least a significant difference ($p < 0.05$) between two hotspots that was confirmed by ANOVA (see Table S2.4). Data of all variables were normalized using the equation: $x_{norm} = (x - x_{min})/(x_{max} - x_{min})$. The descriptive statistics of all variables with original units are shown in Table S2.4 (Supplementary Information)

Located mainly in the Central Highlands, *hotspot type A1* (red pixels in Figure 2.4a) shows soil potential and a stable population, but a high poverty prevalence (Figure 2.3, Table S2.4 in Supplementary Information). About 36% of the degraded agricultural area belongs to this hotspot type. *Hotspot types A2 and A3*, occupying about 25% and 20% of the total degraded agricultural area, respectively, represent the poor rural areas of the Mekong River Delta. With respect to the geographical distribution, hotspot A3 is located in a more remote area, with a poor transportation network, compared to the A2 type. *Hotspot type A4* was found in steep and remote mountains and very poor rural areas in the Northwest region of the country (mainly Son La province) (see the purple pixels in Figure 2.4a). Although sparsely populated, this area suffers the lowest GDP per capita and poverty prevalence, compared to the other hotspots (Figure 2.3, Table S2.4 in Supplementary Information). *Hotspot type A5* is located near urban areas, with a limited area (only 768 $km^2$, or about 4% of the degraded agricultural area), characterized by high speed of urbanization (associated with conversions from crop to residential land), medium economic growth, and less poverty. *Hotspot type A6* is specified for new economic development (Binh Duong province), with remarkable progress in rural poverty alleviation.

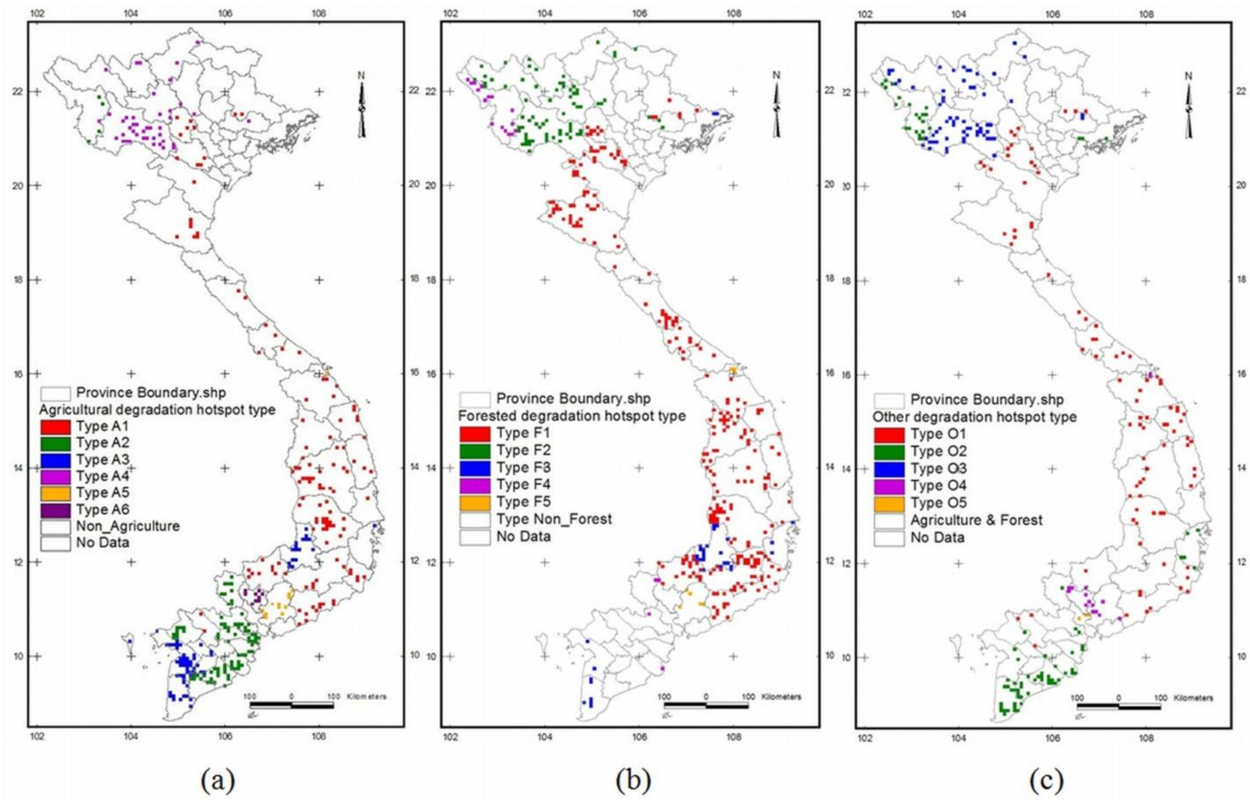


**Figure 2.4** Spatial distribution of social–ecological degradation types in (a) agricultural land, (b) forested land, and (c) severely degraded land.

*Types of degradation hotspots in forest land*

There were 389 degraded pixels (24,896 km$^2$, or about 40% of the total degraded area) found in the forest area. About 20% of the total degraded forest area (i.e., 78 pixels) has had the average LAI of the whole study period greater than 4, meaning a saturate NDVI–biomass relationship. Thus, the calculated trend in this NDVI saturated zone may be biased for indicating biomass productivity. Biomass productivity in more than 90% of this degraded forest area was constrained by limitations in soil nutrient availability and nutrient retention capability (see Table 2.3). About 66–69% of the area has poor root conditions (e.g., shallow top soils and high stoniness), which causes a high demand for work power for replanting efforts, as well as difficulties for natural tree regeneration.

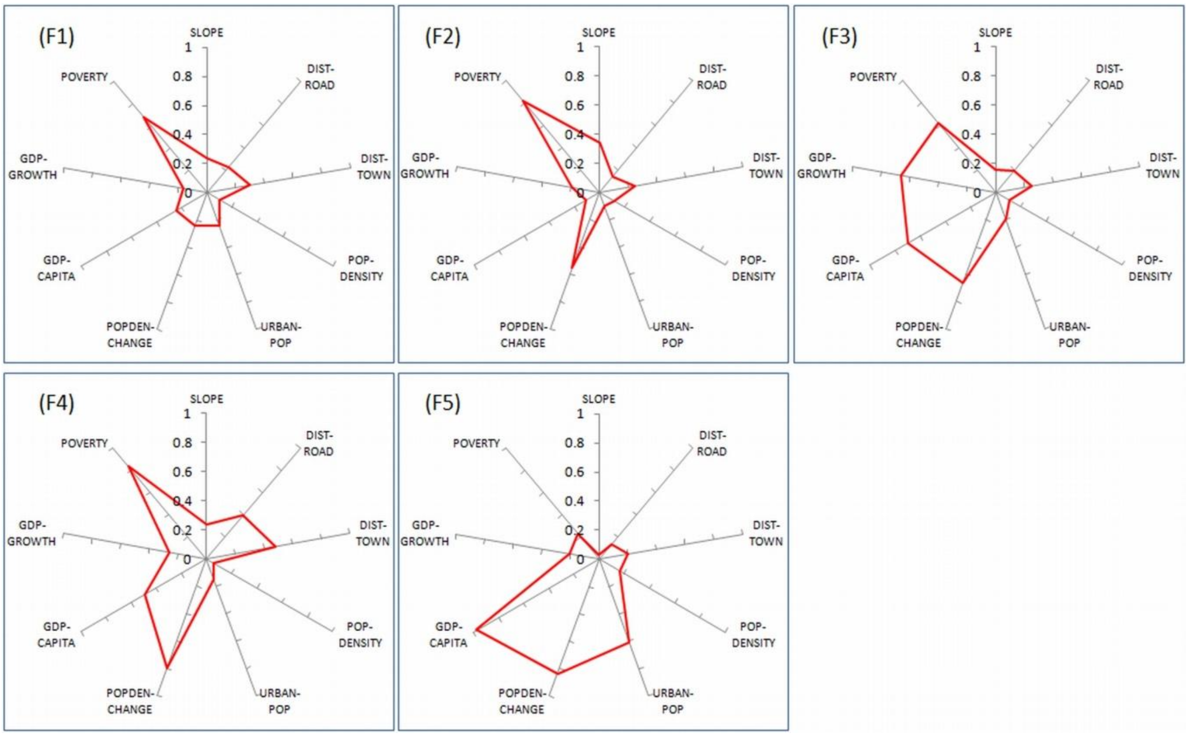


**Figure 2.5** Spider diagrams showing main socio and ecological variables of five degradation hotspot types in forest land. Notes: The figure shows only variables with at least a significant difference ($p < 0.05$) between two hotspots that was confirmed by ANOVA (see Table S2.5). Data of all variables were normalized using the equation: $xnorm = (x - xmin)/(xmax - xmin)$. The descriptive statistics of all variables with original units are shown in Table S2.5 (Supplementary Information)

Cluster analysis using eleven social and ecological variables differentiated five degradation hotspot types in the forest zone. Statistical characterization of these hotspot types is shown in Figure 2.5 and Table S2.5 (in Supplementary Information), and their spatial distribution is illustrated in Figure 2.4b.

Areas of *hotspot type F1* (65% of the degraded forest area) are scattered along the central part of the country, characterized by steady population density, but highly rural poverty (Figure 2.5, red pixels in Figure 2.4b). *Hotspot type F2* (19% of the degraded forest area) was found in steep and remote mountains and very poor rural areas in the Northwest Mountains. Similar to the *A4* type, type *F2* is dominant in Son La province (see the green areas in Figure 2.4b). *Hotspot type F3* (9% of the degraded forested area) is located in a new province in the Central Highlands (Dak Nong province), which has shown rapid economic growth in the urban zones but has a high prevalence of poor rural zones as well. The factor that differentiates this hotspot type from others is the high growth rate of GDP per capita (see Figure 2.5 and Table S2.5 in Supplementary Information). *Hotspot type F4* (5%) was found in another new province (Dien Bien province), in the steep and very remote Northwest mountains, with low population and high rural poverty. *Hotspot type F5* (only 2% of the degraded forest area) is associated with forest areas near urban (facing rapid urbanization) areas showing medium economic growth and less poverty, in forested areas around the cities of Da Nang and Dong Nai.

A common characteristic of all forest degradation types is that they are all located in protected areas, indicating inefficiency in the management of natural reserves and national parks in the country during the past 25 years.

*Hotspot types in severely degraded land*

About 25% of the total human-induced degradation area was found in severely degraded lands. These lands include (i) seriously degraded farmlands with no, or very low, agricultural usability; and (ii) denuded hills and mountains that do not seem to have any potential for natural restoration of biomass production within the next decades, unless some reclamation efforts (e.g., afforestation) are made. About 76–79% of the area faces either moderate or high severities of soil nutrient availability and nutrient retention capability (Table 2.3). The degraded area has also suffered soil constraints in root condition and workability for agricultural production (47–48% of the degraded area), as well as some terrain constraints (22%) (Table 2.3).

Five types of hotspots in severely degraded land were identified, as shown in Figure 2.4c and 2.6, and Table S2.6 (Supplementary Information). *Hotspot type O1* (about 35% of the degraded area) is scattered throughout different parts of the country and characterized by high poverty prevalence. *Hotspot type O2* (32% of the degraded area) was found mainly in some remote areas of the Northwest mountains and Mekong River Delta, and it is characterized by stable demography and medium poverty prevalence. *Hotspot type O3* is located mainly in Son La province, in the Northwest region, characterized by steep and remote mountains and very high poverty prevalence. *Hotspot type O4* (6% of the degraded area) is near urban areas characterized by high urbanization speed, medium economic growth, and less poverty, mainly in Dong Nai and Binh Duong provinces. *Hotspot type O5* was found in tiny areas (1% of the degraded area) around Ho Chi Minh City, the biggest urban area in Vietnam, which has seen very high population density and fast economic growth in the past decade.

## 2.4 Discussion

### 2.4.1 New features of the used method

Validation for whether inter-annual GIMMS NDVI trends can indicate the temporal trend of NPP was a gap in formerly reported studies which assessed biomass productivity degradation using NDVI time-series. Many of these studies, such as those reported by Herrmann et al. (2005), Helldén and Tottrup (2008), and Vlek et al. (2010), only assumed a strongly positive relationship between NDVI and NPP trends based on reviews of literature that was not necessarily consistent with the geographic scales and climate regions considered. Bai et al. (2008b) reported a strong spatial relationship between mean annual GIMMS NDVI and MODIS NPP across the globe. However, since the relationship was derived from a very large number of pixels across the globe, we expected it to be statistically significant. Yet this does not necessarily indicate a strong relationship between GIMMS NDVI and MODIS NPP on an annual, per-pixel basis, which may be incorrectly inferred (Vogt et al., 2011; Wessels, 2009). As NDVI values can be affected by several site-specific factors, such as plant canopy characteristics, life-form and species compositions (Markon et al., 1995; Mbow et al., 2013; Pinter et al., 1985), topography and altitude (Thomas, 1997), different locations with the same NDVI value are not necessary with the same biomass productivity. Thus, comparison of biomass productivity between pixels using NDVI can be a pitfall (Pettorelli et al. 2005). Moreover, correlation between the mean annual NDVI and NPP differs from the matching between the 'inter-annual trends' of the two parameters, which was actually used for the assessment of biomass productivity decline.

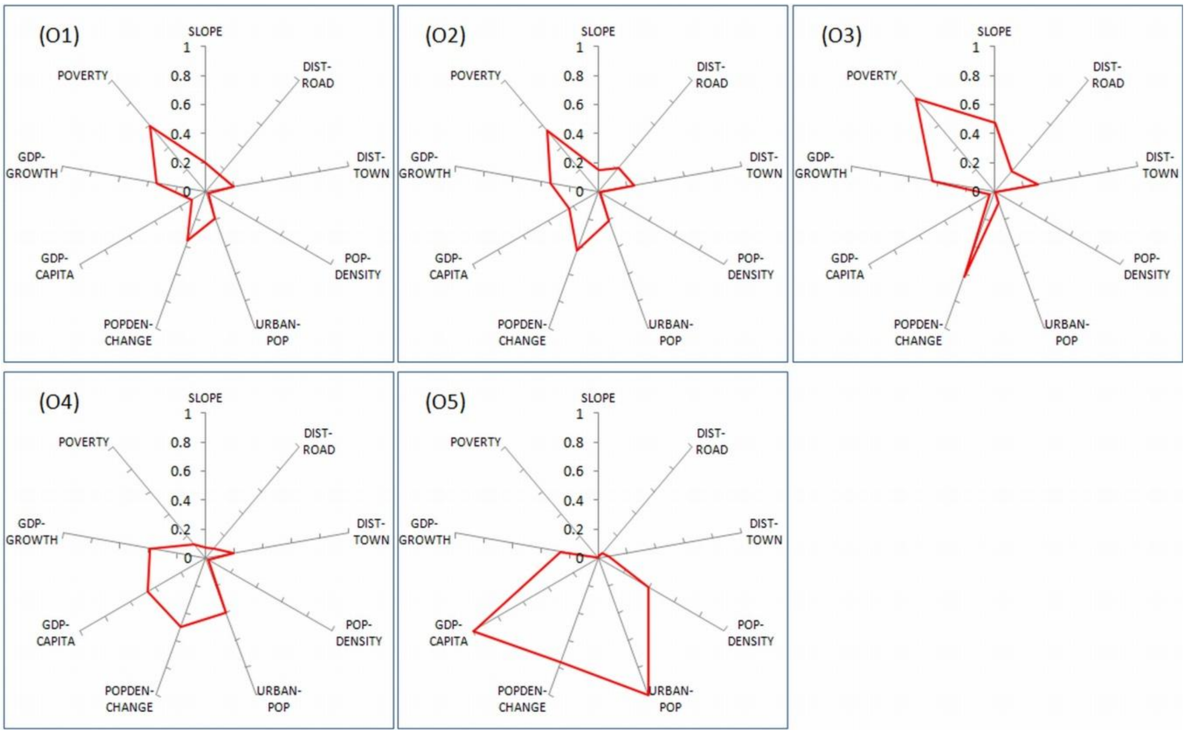


**Figure 2.6** Spider diagrams showing main socio and ecological variables of five degradation hotspot types in severely degraded land. Notes: The figure shows only variables with at least a significant difference ($p < 0.05$) between two hotspots that was confirmed by ANOVA (see Table S2.6). Data of all variables were normalized using the equation: *xnorm = (x – xmin)/(xmax – xmin)*. The descriptive statistics of all variables with original units are shown in Table S2.6 (Supplementary Information)

We validated the NDVI-based biomass productivity degradation assessment using a multi-aspect approach. First, rather than considering the relationship between mean annual NDVI and NPP across space, we evaluated the consistency between the spatial patterns of inter-annual trends of the two parameters as recommended by Wessels (2009). The evaluation results are consistent to those recently found by Zhao and Running (2011). Second, we investigated 'convergent validity' to differentiate declining human-induced biomass productivity from the climate-driven phenomenon. Convergent validity is established when different methods to assess one issue lead to highly correlative results (Scholz and Tietje 2002). The high consistency between the results depicted by the two different methods (i.e., *Trend-Correlation* and *ResTrend*) indicates a good convergent validity for our assessment of human-induced biomass productivity degradation based on long-term time series of NDVI and climate. Third, we compared the assessment result with qualitative and spatially implicit knowledge generated by other studies in different sub-regions. Our findings for biomass productivity degradation hotspots agree at the four priority regions mentioned in the National Action Program to Combat Desertification for the Period 2006–2010 and the Orientation to 2020 (NAP 2006). Comparisons between the spatial pattern of temporal NDVI trends with regional reports of deforestation, forest degradation and agricultural intensification also show good matches.

Analysis of the relationship between the occurrence of biomass productivity degradation hotspots and socio-ecological factors is important as they inform land-use and management policies for mitigating degradation. The way we identify social–ecological types of the degradation hotspots complements previous studies on the issue. Bai et al. (2008b) and Nkonya et al. (2011a) analyzed the relationship between the area of long-term NDVI decline and variables of demography, economic growth and/or poverty. However, they did not map distinct clusters of degraded pixels regarding the considered social and economic variables for guiding follow-up research at finer scales. The studies also did not include important variables such as soil constraints, biophysical and institutional accessibilities. Vlek et al. (2008, 2010) explicitly mapped different types of biomass productivity degradation hot spots across sub-Saharan Africa using a nature-like hierarchical classification system that combines major biophysical variables (e.g., climate zone and soil constraint) and socio-economic variables (e.g., population density and land use type). Classification of degradation hotspots in this way may be appropriate for a limited number of considered affecting factors at very large scale (e.g., continent), and comprehensive for lay stakeholders to follow. However, the number of clusters can be plentiful with a few classifiers, such as 3 classes of climate × 3 classes of soil constraints × 3 classes of population density = 27 combined clusters. At the national level, the relevant factors can be many more than the three factors mentioned, resulting in numerous clusters to interpret. Moreover, the approach has yet to utilize the advantage of continuous scale of several variables in the classification procedure. Our reported work complements the above-mentioned studies in offering a feasible way to spatially delineate and characterize a limited number of distinct degradation types regarding multiple social and ecological dimensions that are important for formulating further region-specific research.

### 2.4.2 Contextualization of the empirical findings and implications for land degradation combating policy

Mapping social–ecological hotspots of environmental problems across regional or national scale is essential for improving environmental management planning and policies (Alessa et al., 2008; Liu et al., 2008). Considering in the socio-ecological characterization of hotspot types, the results showed that the upland and mountain regions of Vietnam, where there is high risk of soil erosion and land management is poor, have suffered most extensive and severe land degradation. This supports the findings of earlier studies in Vietnam (De et al., 2008; Vezina et al., 2006; Wezel et al., 2002b). The distribution of soil constraints over three degraded zones demonstrates that constraints in soil nutrient availability and nutrient retention capability are widely dominant in all degradation hotspot types, as generally mentioned by Bo et al. (2003a). However, being different from that the other studies advocated the above-mentioned knowledge were based on small scale, short-term analyses or expert-based assessments, our finding was driven from a rigorously quantitative analysis over the long-term (25 years) and across the whole country.

The findings that the most extensive areas of severe land degradation (i.e., the Northwest and Central Highlands) were characterized by low population density, very low GDP per capita and very high poverty index show consistencies with the patterns reported by other studies on the same topic (Bai et al., 2008b; Jorgenson, 2006; Nkonya et al., 2011a; Vlek et al., 2010). The pattern may be explained by different co-existing mechanisms. First, the biophysical setting of these regions constitutes fragile lands with limiting carrying capacities [3] that are easily overpopulated (Jamieson et al., 1998; Vlek et al., 2010). Second, poor law enforcement and land-use management lead to unsustainable land-use activities such as forest clearance, logging and wide-spread slash-and-burn cultivation on steep areas that lead to severe soil degradation (Jamieson et al., 1998; Le, 2005). Third, the poor economic development, lack of manpower, poor access to knowledge and conservation technology, as well as low social incentives for forest and soil conservation have constrained land restoration. Finally, rapid urbanization in the cities and increased exportation of agricultural and timber products have created a 'tele-effect' on deforestation and forest degradation in the remote and low populated mountains (DeFries et al., 2010; Jorgenson, 2006).

The findings suggest important aspects for improving policies directed toward mitigating land degradation in Vietnam. The defined location of the degradation hotspots may help land-use policy makers and planners to target the degraded areas better, thereby optimizing their limited budget for mitigating land degradation. This complements the non-spatial highlights of the National Action Program to Combat Desertification for the Period 2006–2010 and Orientation to 2020 (NAP, 2006). The multi-dimensional characterization of the degradation hotspots suggests important region-specific factors that need to be considered in the formulation of a relevant policy. For instance, the rural areas in the Mekong River Delta have a high bio-physical potential for agricultural production and higher carrying capacity than the uplands. The most striking constraints are that the region is facing a high degree of poverty, and poor access to education, financial services, and markets (associated with underdeveloped infrastructure). A land degradation mitigating policy for this area may need to focus on the improvement of rural credit systems for conservation agriculture (e.g. organic rice, aquaculture and fruit productions), development of regional market networks for eco-agro products, along with educational and infrastructure development in the long-term. Particular focus should be on the Northwest, as it suffers from the lowest GDP per capita and poverty, while at the same time its ecosystems are highly fragile, with a low carrying capacity due to high soil erosion risks. Food security in these areas will be threatened since population density continues to increase. This situation could be controlled if measures of increasing the carrying capacity for these regions are considered adequately, or the pressures on land are reduced. The Northwest further needs priority strategies on poverty alleviation and hunger eradication, e.g. in the form of reclaiming unused land, raising and reserving forest areas, creating jobs and increasing incomes for the poor in very remote rural areas.

[3] Carrying capacity is the size of the population that can be supported indefinitely by a land ecosystem without destroying it

### 2.4.3 Limitations of the method used and improvement strategy

Similar with many other studies on land productivity assessment using remote sensing and climate time-series, our method has certain limitations. The first limitation is that the analysis of inter-annual NDVI trends was based on the linearity assumption for the phenomenon (Bai et al., 2008b; de Jong et al., 2011; de Jong et al., 2012; Helldén and Tottrup, 2008; Le et al., 2012b; Li et al., 2012; Wessels et al., 2007). The linear trend statistics may not be able to capture persistent, but convex or concave, changes in annual mean NDVI over the long term. Although non-linear trend analysis techniques are available (Wu et al., 2007), so far the techniques have only been applied for investigating market, population and climate dynamics in a non-spatial way rather than on a pixel basis. Pixel-based, non-linear trend analysis of land productivity remains a fruitful research topic for the land degradation research community.

The second limitation is that we have not yet incorporated the masking effects of either atmospheric fertilization and human use of fertilizers on soil fertility in long-term. Given that the atmospheric fertilization (e.g., elevated $CO_2$ in the air and $NO_x$, $NH_4$ deposition on the land surface) has positively affected the vegetation greenness (Buitenwerf et al., 2012; Higgins and Scheiter, 2012; Le et al., 2012b; Vlek et al., 2010) and this foliage effect of atmospheric fertilization does not necessarily correlate to soil improvement, this phenomenon can mask the NDVI-based biomass productivity degradation assessment. Increasing use of fertilizers during the agricultural intensification process in Vietnam's river deltas during the last 20 years may also be another important masking effect in our degradation assessment. The use of NPK fertilizer in Vietnam increased from 59 ton/ha/yr in 1985 to 255 ton/ha/yr in 2000 (calculated from Bo et al. (2003a)). Improvement of crop yield in intensified farming areas of the Red River Delta and Mekong River Delta seems to be mainly driven by the increase of external fertilizer and water inputs and the use of high-yield crop varieties, and not necessarily by improving soil fertility. Given the two types of masking effects, the actual degraded area might be more extensive than what has been reported in this study. Follow-up efforts for correcting the masking effect of atmospheric fertilization using the method proposed by Vlek et al. (2010) and Le et al. (2012b) will require the examination of intact vegetation areas (where biomass improvement can be attributed to atmospheric fertilization effect). As it is difficult to find intact vegetation areas in Vietnam, expanding the study area to the whole Indochina Peninsula may help to apply the method. Correction of the masking effect caused by human use of fertilizers can be done by analyzing the response of crop yield to fertilizers based on experimental data. However, this follow-up work is possible only at finer scale (e.g. farm and watershed scales), rather than the resolution in this large-scale assessment (i.e., 64 $km^2$).

Third, the validation of the NDVI–NPP relationship is still limited to indirect reference NPP data (MODIS NPP) and qualitative judgments using precedent national publications, rather than ground measured data. Thus, the first step of follow-up studies should be ground-true surveys or field monitoring for validating the delineated hotspots, such as the exemplar work done recently by Mbow et al. (2013). As these ground-based validations are time-consuming and can be made only at field or local landscape levels, well-justified geographic foci for site selection become important. In prior to our reported work, it would be difficult to do so given the spatially implicit and subjective results of NAP (2006). The benefit of our work is that we provide the first version degradation hotspots map, though it is still "potential" in some degree, and the social–ecological types of the hotspots that guide policy makers about where to invest on ground-based validations in a systematic, cost-effective way.

Fourth, due to the lack of temporal vegetation data at national level, the presented study has not considered the effects of changes in vegetation structure (e.g. life-form spectrum and species composition) on the NDVI–NPP relationship. These changes were possible along with natural successions or human-induced land cover changes (e.g. selective logging) over the past three decades, which may weaken the positive NDVI–NPP relationship (Mbow et al. 2013). Efforts to incorporate these confounding effects can be made only in follow-up studies at field and local landscape scales where detailed vegetation data can be gathered.

The social and ecological factors associated with the identified hotspot types reflect correlative relationships between them and biomass productivity degradation, and have not yet been proven as causal factors. However, our findings suggest explicitly hypotheses for region-specific causes of biomass productivity degradation in follow-up cause-effect analyses at the national and hotspot scales. The follow-up analysis of social–ecological causes of biomass productivity decline for each land-use stratum is showed in a companion paper (Vu et al., 2014a). Moreover, the relationships between NDVI or NPP trend and other important processes of land degradation (e.g. soil erosion, nutrient depletion) have not yet been investigated in this study, thus should be the subject for follow-up studies. However, the investigation of the relationships requires research methods such as the assessment and modeling of soil erosion, nutrient leaching, crop yield dynamics and nutrient balances in different agro-ecosystems that demand new datasets collected at landscape and farm scales. These detailed studies are costly and it is impractical to do them across the nation. The findings of our nation-wide screening assessment provide a comprehensive geographic frame for systematically formulation a 'spectrum of representative regional cases' for feasible follow-up research.

## 2.5 Conclusions

This study identified and classified geographic hotspots of human-induced biomass productivity degradation in Vietnam, which can be used to guide future, smaller-scale land degradation studies. With the geographic hotspot approach, the goal of this study is to delineate the areas of most prevailing degradation to help prioritize resources allocation in policies for combating land degradation, as well as investments on more detailed assessment at lower levels (i.e., regional and local). By focusing on areas with strong, clear trends of biomass productivity of the land, the geographic hotspot approach helps avoid confounding effects of factors with no contribution to land degradation that are not well-controlled in a single, proxy indicator method here-used.

We used a long-term trend (1982–2006) in inter-annual AVHRR NDVI as a proxy for measuring the decline or improvement in biomass productivity on a national scale. By analyzing the temporal correlation between climate factors (rainfall and temperature) and NDVI time-series over the last 25 years, we isolated areas affected by human-induced productivity decline from those in which the decline is driven by climate dynamics. Our results were validated by different approaches. The spatial pattern of inter-annual AVHRR NDVI trends was similar to those of temporal MODIS NPP trends. The two different methods used to assess human-induced productivity decline (*Trend-Correlation* and *ResTrend*) produced the same results, indicating a high confidence level for the applied methodology. We further found consistency between our spatial pattern of temporal NDVI trends and reported regional data for forest degradation and agricultural intensification.

We delineated areas of about 63,900 $km^2$ of land (19% of the national land) showed a persistent decline in biomass productivity that was mainly caused by non-climate (i.e., anthropogenic) factors. The largest degraded areas were found in the Southeast, the Mekong River Delta, the Northwest Mountains, and the Central Highlands. Besides being in good agreement with four priority regions mentioned in the National Action Programme to Combat Desertification for the Period 2006–2010 and orientation to 2020 (NAP, 2006), our results are spatially explicit and should support land-use policy makers and planners in better targeting the degraded areas and optimizing their limited budgets. The identified hotspots also help prioritize areas for further studies at finer scales that help understand about the processes and drivers involved deeper, more comprehensive; in turn resulting in the next improved version of land degradation pattern in Vietnam With the proxy nature of the used indicator and the coarse resolutions of used ecological–social characterizing variables, there may be some degraded areas outside of the detected hotspots, and some areas within the hotspots may not be severely degraded. However, if the reported result is adopted, the risk of wrong geographical prioritization in national policy and research efforts toward combating land degradation will likely be much lower compared to the risk of decision made based on the baseline knowledge (before this study).

Using spatial cluster analysis with spatial multivariate data for the detected degradation areas, we located and characterized the area clusters of human-induced biomass productivity degradation associated with different profiles of socio-ecological factors. Constraints in soil nutrient availability and nutrient retention capability are widely spreading in all degradation hotspot types. These hotspot types differ from each other in terms of social and ecological affecting factors, suggesting that region-specific strategies are needed both in future research and governance approaches tackling land degradation.

## Appendix A. Supplementary Information

**Table S2.1** Main land-use types aggregated from the original classes (levels 1 to 3) of the National Land Use Map of Vietnam 2005.

| Class and sub-class in National Land Use Map of Vietnam 2005 | Broad land-use types used in this study |
|---|---|
| **1. Agriculture land** | |
| 1.1. Agriculture production land | |
| 1.1.1 Annual crop land | Agricultural land |
| 1.1.2. Pasture | Agricultural land |
| 1.1.3. Other annual crop land | Agricultural land |
| 1.1.4. Perennial crop land | Agricultural land |
| 1.2. Forestry land | |
| 1.2.1. Productive forest | Forest land |
| 1.2.2. Protective forest | Forest land |
| 1.2.3. Special use forest | Forest land |
| 1.3. Aquaculture | (*masked in this study*) |
| 1.4. Salt fields | (*masked in this study*) |
| 1.5. Other agricultural lands | Agricultural land |
| **2. Non-agriculture lands** | |
| 2.1. Residential land | (*masked in this study*) |
| 2.2. Land for special purposes | (*masked in this study*) |
| 2.2.1. Offices | (*masked in this study*) |
| 2.2.2. Military | (*masked in this study*) |
| 2.2.3. Security | (*masked in this study*) |
| 2.2.4. Non-agriculture business | (*masked in this study*) |
| 2.2.5. Parks in urban, historical spots | (*masked in this study*) |
| 2. 3. Religion and belief construction | (*masked in this study*) |
| 2.4. Cemetery | (*masked in this study*) |
| 2.5. Water flows and surfaces for special purpose | (*masked in this study*) |
| 2.6. Other non-agriculture lands | (*masked in this study*) |
| **3. Un-used land** | |
| 3.1. Un-used lowland | Other land |
| 3.2. Un-used upland | Other land |
| 3.3. Rocky mountains | (*masked in this study*) |
| **4. Coastal water surfaces** | |
| 4.1. Coastal area for aquaculture | (*masked in this study*) |
| 4.2. Coastal area with mangrove forest | Forest land |
| 4.3. Coastal area for other purposes | (*masked in this study*) |

**Table S2.2** Soil qualities and related soil characteristics (Source: Fischer et al., 2008)

| *Soil Quality* | *Soil Characteristics*[a] |
|---|---|
| Nutrient availability | Soil texture, soil organic carbon, soil pH, total exchangeable bases |
| Nutrient retention capacity | Soil Organic carbon, soil texture, base saturation, cation exchange capacity of soil and of clay fraction |
| Rooting conditions | Soil textures, bulk density, coarse fragments, vertic soil properties and soil phases affecting root penetration and soil depth and soil volume |
| Oxygen availability to roots | Soil drainage and soil phases affecting soil drainage |
| Excess salts | Soil salinity, soil sodicity and soil phases influencing salt conditions |
| Toxicity | Calcium carbonate and gypsum |
| Workability (constraining field management) | Soil texture, effective soil depth/volume, and soil phases constraining soil management (soil depth, rock outcrop, stoniness, gravel/concretions and hardpans) |

[a] Meaning of the involved soil characteristics for determining the considered soil quality can be found in http://www.fao.org/nr/land/soils/harmonized-world-soil-database/soil-quality-for-crop-production/en/

**Table S2.3** Reclassification of the FAO/IIASA's severity scale for soil quality constraints

<table>
<tr><th>Soil quality</th><th>GAEZ's constraint class</th><th>Reclassified class (used in this study)</th></tr>
<tr><td rowspan="4">Severity class applied for specific criteria of soil quality (GAEZ 2008 data) (Fischer et al., 2008)</td><td>No or slight constraints</td><td>No or slight constraints</td></tr>
<tr><td>Moderate constraints</td><td>Moderate constraints</td></tr>
<tr><td>Severe constraints</td><td rowspan="2">Severe/very severe constraints</td></tr>
<tr><td>Very severe constraints</td></tr>
<tr><td rowspan="7">Severity class applied for combined soil constraints (GAEZ 2002 data) (Fischer et al., 2002)</td><td>No constraints</td><td rowspan="3">No or slight constraints</td></tr>
<tr><td>Very few constraints</td></tr>
<tr><td>Few constraints</td></tr>
<tr><td>Partly with constraints</td><td>Moderate constraints</td></tr>
<tr><td>Frequent severe constraints</td><td rowspan="3">Severe/very severe constraints</td></tr>
<tr><td>Very frequent severe constraints</td></tr>
<tr><td>Unsuitable for agriculture</td></tr>
</table>

**Table S2.4** Socio-ecological characterization of degradation hotspot types in agricultural land

| *Variable* | *Agricultural degradation type (N = 338 degraded pixels)* | | | | | |
|---|---|---|---|---|---|---|
| | *Type A1 (n= 122)* | *Type A2 (n= 85)* | *Type A3 (n= 68)* | *Type A4 (n= 42)* | *Type A5 (n= 12)* | *Type A6 (n= 9)* |
| SLOPE* | 3 ± 1 | 1 ± 1 | 2 ± 1 | 13 ± 3 | 2 ± 1 | 2 ± 1 |
| SOIL-CONSTRAINT | 2 | 3 | 3 | 3 | 3 | 3 |
| PROTECTION | 0 | 0 | 0 | 0 | 0 | 0 |
| DIST-ROAD* | 5.9 ± 1.3 | 7.1 ± 1.1 | 7.4 ± 2.0 | 4.3 ± 1.3 | 2.3 ± 0.7 | 4.8 ± 2.3 |
| DIST-TOWN* | 11.6 ± 1.3 | 8.3 ± 1.2 | 11.1 ± 1.4 | 13.0 ± 2.2 | 7.8 ± 3.1 | 16.7 ± 5.0 |
| POP-DENSITY* | 253 ± 55 | 384 ± 80 | 248 ± 49 | 103 ± 35 | 428 ± 268 | 167 ± 110 |
| URBAN-POP* | 0.23 ± 0.01 | 0.19 ± 0.01 | 0.22 ± 0.01 | 0.13 ± 0.01 | 0.35 ± 0.08 | 0.28 ± 0.00 |
| POPDEN-CHANGE* | 12 ± 1 | 16 ± 3 | 16 ± 4 | 25 ± 2 | 37 ± 1 | 7 ± 0 |
| GDP-CAPITA* | 3376 ± 38 | 4931 ± 55 | 5981 ± 67 | 2444 ± 79 | 7929 ± 48 | 9389 ± 0 |
| GDP-GROWTH* | 15.7 ± 0.7 | 14.3 ± 0.5 | 22.4 ± 3.4 | 16.2 ± 0.5 | 16.9 ± 0.4 | 16.1 ± 0.0 |
| POVERTY* | 0.52 ± 0.03 | 0.40 ± 0.04 | 0.44 ± 0.02 | 0.76 ± 0.06 | 0.14 ± 0.05 | 0.10 ± 0.04 |

Note: * indicates there is at least a significant difference ($p < 0.05$) in the corresponding variable between two hotspots that was confirmed by ANOVA.
The uncertainty range is the confidence interval of the mean at 95% level ($p < 0.05$).

**Table S2.5** Socio-ecological characterization of hotspot types in forest land

| *Variable* | *Forest degradation type (N = 389 pixels)* | | | | |
|---|---|---|---|---|---|
| | *Type F1 (n=253)* | *Type F2 (n=74)* | *Type F3 (n=34)* | *Type F4 (n=20)* | *Type F5 (n=8)* |
| SLOPE* | 12 ± 1 | 17 ± 2 | 8 ± 3 | 12 ± 4 | 1 ± 1 |
| SOIL-CONSTRAINT | 3 | 3 | 3 | 3 | 3 |
| PROTECTION | 1 | 1 | 1 | 1 | 1 |
| DIST-ROAD* | 11.2 ± 1.1 | 6.7 ± 1.4 | 9.4 ± 2.4 | 18.9 ± 7.1 | 6.5 ± 2.9 |
| DIST-TOWN* | 17.9 ± 1.1 | 15.2 ± 1.8 | 15.4 ± 2.3 | 27.7 ± 6.9 | 12.7 ± 2.5 |
| POP-DENSITY | 60 ± 12 | 69 ± 17 | 63 ± 35 | 35 ± 30 | 99 ± 66 |
| URBAN-POP* | 0.23 ± 0.01 | 0.14 ± 0.01 | 0.20 ± 0.03 | 0.17 ± 0.00 | 0.48 ± 0.18 |
| POPDEN-CHANGE* | 11 ± 1 | 23 ± 2 | 28 ± 6 | 33 ± 5 | 35 ± 3 |
| GDP-CAPITA* | 3353 ± 26 | 2464 ± 73 | 6239 ± 106 | 4938 ± 63 | 8006 ± 114 |
| GDP-GROWTH* | 16.0 ± 0.5 | 17.0 ± 0.7 | 34.7 ± 5.7 | 19.4 ± 1.0 | 17.6 ± 1.0 |
| POVERTY* | 0.68 ± 0.03 | 0.82 ± 0.03 | 0.63 ± 0.06 | 0.83 ± 0.12 | 0.27 ± 0.20 |

Note: * indicates there is at least a significant difference ($p < 0.05$) in the corresponding variable between two hotspots that was confirmed by ANOVA.
The uncertainty range is the confidence interval of the mean at 95% level ($p < 0.05$).

**Table S2.6** Socio-ecological characterization of hotspot types in severely degraded land

| *Variable* | *Hotspot type (N = 251 degraded pixels)* | | | | |
|---|---|---|---|---|---|
| | *Type O1 (n=89)* | *Type O2 (n=81)* | *Type O3 (n=63)* | *Type O4 (n=15)* | *Type O5 (n=3)* |
| SLOPE* | 8 ± 2 | 6 ± 2 | 18 ± 2 | 3 ± 2 | 1 ± 1 |
| SOIL-CONSTRAINT | 3 | 3 | 3 | 3 | 3 |
| PROTECTION | 0 | 0 | 0 | 0 | 0 |
| DIST-ROAD* | 7.6 ± 1.8 | 10.6 ± 2.4 | 9.0 ± 2.1 | 4.5 ± 2.0 | 2.2 ± 3.2 |
| DIST-TOWN* | 12.0 ± 1.6 | 15.1 ± 2.7 | 18.0 ± 2.9 | 11.7 ± 3.3 | 4.8 ± 7.2 |
| POP-DENSITY* | 454 ± 334 | 200 ± 42 | 98 ± 65 | 266 ± 180 | 7359 ± 24244 |
| URBAN-POP* | 0.21 ± 0.01 | 0.22 ± 0.02 | 0.13 ± 0.01 | 0.35 ± 0.09 | 0.78 ± 0.00 |
| POPDEN-CHANGE* | 15 ± 2 | 17 ± 3 | 25 ± 2 | 20 ± 8 | 30 ± 0 |
| GDP-CAPITA* | 3357 ± 49 | 5304 ± 147 | 2401 ± 77 | 8733 ± 405 | 16804 ± 0 |
| GDP-GROWTH* | 15.8 ± 0.86 | 15.6 ± 0.68 | 17.5 ± 0.74 | 16.7 ± 0.55 | 14.5 ± 0.00 |
| POVERTY* | 0.59 ± 0.04 | 0.56 ± 0.06 | 0.83 ± 0.04 | 0.16 ± 0.05 | 0.05 ± 0.04 |

Note: * indicates there is at least a significant difference ($p < 0.05$) in the corresponding variable between two hotspots that was confirmed by ANOVA.

The uncertainty range is the confidence interval of the mean at 95% level ($p < 0.05$).

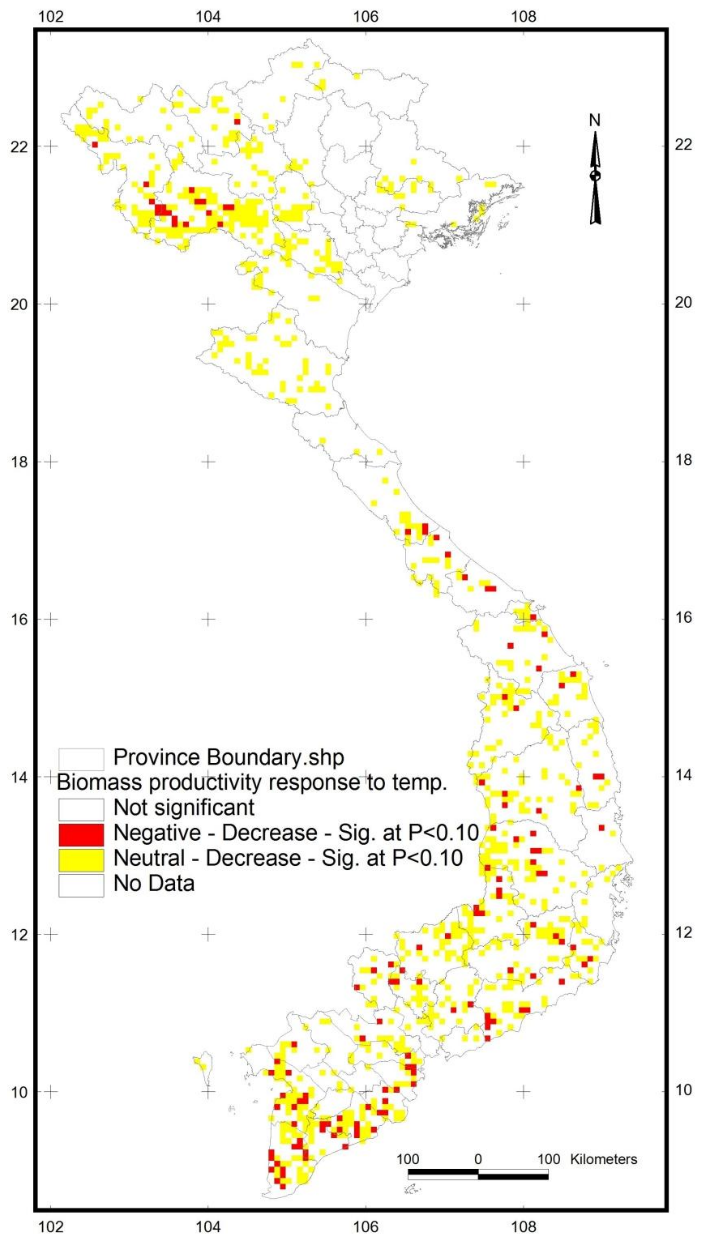


**Figure S2.1** Inter-annual NDVI–temperature correlation in the area of NDVI decline. About 87% of degraded area across the country has not been associated significantly with temperature reduction.

# 3. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level *


## Abstract

Recognizing the socio-economic and biophysical causes of land degradation at the national level is important for cause-targeted strategies when designing policies for combating land degradation. This study aims to identify the biophysical and socio-economic factors that significantly affect land degradation across Vietnam and to interpret the causalities underlying the effects. The dependent variables considered in the study are spatial, the extent and intensity of degradation in three land-use zones (agriculture, forest and severely degraded abandonment). The hypothesized explanatory variables are common economic and demographic drivers and bio-physical factors such as soil, terrain constraints, and neighborhood land-use structures that are often neglected in many large-scale land degradation assessments. Instead of using a single inferential statistic technique, we used multi-linear regression and binary logistic regression in a complementary manner to increase the detectability and credibility of the degradation cause analyses. The results showed agricultural production growth had strong and consistent effects on land degradation extent and intensity. Population growth, especially in rural areas, had a strong effect on the extent of overall land degradation. The importance of a neighboring forest was revealed for its ability to reduce land degradation intensity in abandoned, unproductive lands. The concrete faceting of the causal analysis for each land-use zone as social–ecological stratum allowed us to combine the defined social–ecological contexts, contemporary theories, and hypotheses in the field to clarify the causal factors of a complex phenomenon like land degradation. The study demonstrates these contemporary inferential statistics can be complementarily used to sufficiently detect and understand land degradation causes at the national level. The results suggest implications for national land management policy: internalizing land degradation costs in the farming system evaluation for payment for ecosystem services policy, restricting forest conversion, and improving extension services and education in agrarian communities.


* This chapter has been published as:
Vu, Q.M., Le, Q.B., Frossard, E., Vlek, P.L.G., 2014. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level. Land Use Policy 36, 605-617. DOI: 10.1016/j.landusepol.2013.10.012

## 3.1 Introduction

Land degradation is defined as the persistent reduction or loss of the land's ecosystem services, notably primary production service (Vogt et al., 2011). Land degradation is caused by both natural and anthropogenic phenomena (Le et al., 2012b; Vlek et al., 2008; Vu et al., 2012a) where the former is balanced by natural processes and cannot be interfered with and the latter can be mitigated, even though it is a difficult task (Stocking and Murnaghan, 2001).

The problems of land degradation are most serious in tropical regions, where communities' livelihoods depend on land productivity (e.g., food production and products from forests) and the land and soil resources are exposed to natural constraints (e.g., high annual rainfall and steep terrain conditions). Tropical regions are also home to the poorest communities in the world, where there is a downward spiral between poverty and land degradation: poverty and economic marginalization lead to land degradation, and land degradation leads to further poverty (Scherr, 2000). Vietnam can be seen as a prevailing case of anthropogenic land degradation. Though agriculture remains the most important sector of the Vietnamese economy, agricultural land area per capita is, on average, about 0.11 ha/person (GSO, 2009). Given this high land pressure, land degradation is one of the most striking problems for the nation, as at least 64,000 $km^2$ of land (19% of the national land mass) experienced persistent declines in biomass productivity over the last 25 years (Vu et al., 2014b). As the land resources in Vietnam are limited and many areas are degraded, one of the top questions for national policy-makers is how to use the land in a sustainable manner, especially for the mountainous and hilly areas, where the land potential is high, but the degradation is serious (Siem and Phien, 1999).

Combating land degradation by formulating effective mitigating policies requires the identification of the anthropogenic causes of the phenomenon (Vlek et al., 2008; Vlek et al., 2010; Von Braun et al., 2012). Although the general categories of land degradation causes have been reviewed (Geist and Lambin, 2004; Nkonya et al., 2011a), comprehensive portfolios of the actual causes and the understanding of their causalities are still lacking (Von Braun et al., 2012). At global level, the Global Assessment of Human-Induced Soil Degradation (GLASOD) (Oldeman et al., 1991) identified the causes of land degradation based on expert opinions that had less scientific rigor. Furthermore, the GLADSOD results are outdated. Some recent global or continental studies used quantitative analyses, but are still limited to the measurement of the correlations between socio-economic factors to indicators of land degradation (e.g. Bai et al., 2008b; Vlek et al., 2008, 2010) that are indeed not an scientific inference of degradation causes. Recently, Nkonya et al. (2011a) used inferential statistics (i.e., multiple linear regressions) to analyze the relationship between a range of biophysical and socio-economic factors and vegetation greenness decline throughout in East Asia. However, the authors admitted of that no strong and meaningful causal relationships could be drawn from the regression results due to the absence of a clear land-use context. Barbier (1997) statistically inferred the causes of land degradation in developing countries; however, the study was limited to economic factors. On the national and sub/national scales, a few studies have analyzed the correlation between land degradation and some natural factors and land use management practices, but without appropriate inferential analyses to reason scientifically the cause-effect relationships (Ayoub, 1998). In Vietnam, only a few studies have been conducted to quantify the direct drivers of soil erosion, such as slope, rainfall erosivity, soil erodibility, vegetation cover, and soil conservation measures, which are evident and limited to some specific areas of the country (Ha, 1996; Siem and Phien, 1999). Therefore, a socially–

ecologically comprehensive understanding of the land degradation causes at the national level is lacking.

Previous large scale land degradation studies recognized methodological gaps that should be fulfilled in next research. First, to address the high diversity of social–ecological context over the national or international scale, causal analyses of land degradation should be carried out within social–ecological strata (e.g. broad climate and land-use zones) (Vlek et al., 2008, 2010; Sommer et al., 2011). Second, because the relationship between land degradation and its drivers can be non-linear (Reynolds et al., 2011), inferential statistical techniques used for the causal analysis should be capable to capture such non-linearity. Moreover, many precedent studies on causes of land degradation focus more one demographic, policy/institutional and economic factors and ignore important biophysical variables that either directly affects, or constrain the phenomenon, such as soil and terrain constraints, surrounding land cover and land use (see a mini review by von Braun et al., 2012). This limitation calls for the inclusion of more biophysical factors in causal analyses of land degradation.

Following the above-mentioned directions, this paper aims to identify the biophysical and socio-economic factors that affect significantly the land degradation across Vietnam and to interpret the causalities underlying the effects. Based on this, the paper endeavors to demonstrate the methodological innovations through a comprehensive assessment of the land degradation causes at the national level and suggest the implications for national policies intended to combat land degradation.

## 3.2 Materials and methods

### 3.2.1 Dependent variables and inferential statistical methods

The dependent variables reflect two important dimensions of the land degradation severity: (1) the spatial extent of the land degradation within an administrative unit (district), and (2) the intensity of the land degradation on a location (8 km × 8 km pixel) (Oldeman et al., 1991) (see Table 3.1). We used the pixel-based data for human-induced land degradation in Vietnam (Vu et al., 2012a) to compute these two dependent variables. The data concerned the persistent decline of the biomass productivity of the land over the last 25 years (1982–2006), approximated by the trend of the inter-annual Normalized Differentiate Vegetation Index (NDVI) for every 64 $km^2$ pixel of the land surface. The confounding effect of rainfall variation on the NDVI trend was corrected. The data were validated by comparing with the spatial pattern of the verified Net Primary Productivity (NPP), calculated using another remote-sensing instrument (at a finer resolution) and climate data (Zhao and Running, 2010, 2011), as well as other reported field studies (see details in Vu et al., 2012a).

**Table 3.1** Dependent variables and corresponding inferential statistical methods

| *Dependent variable* | *Source* | *Inferential statistics* |
|---|---|---|
| *Extent of land productivity decline (unit of analysis = district)* | | |
| DEG_SHARE = Share (%) of degraded land area over 1982–2003 | Aggregated from the results of Vu et al. (2012a) | Multiple linear regression |
| DEG_SHARE_L = spreading level of degradation, measured on binary scale: =1 if DEG_SHARE > 20%, = 0 if otherwise | Re-classed from DEG_SHARE; threshold value adapted from Oldeman et al. (1991) | Binary logistic regression |
| *Intensity of land productivity decline (unit of analysis = 8 km × 8 km pixel)* | | |
| DEG_INTEN = Annual reduction of annual mean NDVI (base year) (%) | Taken from the results of Vu et al. (2012a). | Multiple linear regression |
| DEG_INTEN_L = Intensity level of degradation, measured on binary scale: =1 if DEG_INTEN > 10%, = 0 if otherwise | Re-classed from DEG_INTEN; threshold value adapted from Oldeman et al. (1991) | Binary logistic regression |

#### 3.2.1.1 Land degradation extent

Land degradation extent was measured by the percentage of degraded area within an administrative unit (variable *DEG_SHARE*) (*N* = 377 districts). The inferential statistical method applied for this variable was a multiple linear regression analysis.

$$DEG\_SHARE = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \qquad (1)$$

where $X_i$ and $\beta_i$ ($i$ = 1, 2, 3, …, $n$) are explanatory variables and their weights, respectively. Coefficient $\alpha$ is the intercept.

In addition, we considered the degradation extent on a binary scale (variable *DEG_SHARE_L*): minor spreading rate of degradation if the area percentage of degraded land is less than 20% over 25 years (i.e., < 1% annually) (*DEG_SHARE_L* = 0), and there is a significantly spreading rate of degradation otherwise (*DEG_SHARE_L* = 1) (see Table 3.1). This threshold was adapted from the Global Assessment of Human-Induced Soil Degradation (GLASOD) (Oldeman et al., 1991). The causal effects of explanatory factors on this variable were statistically inferred using binary logistic regression, which has the function of the following form:

$$\ln\left(\frac{p(y=1)}{(1-p(y=1))}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \qquad (2)$$

or:

$$p(y=1) = \frac{e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)}}{1+e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)}}$$

where $y$ is *DEG_SHARE_L* and $p$ ($y$ = 1) is the probability of *DEG_SHARE_L* = 1.

The consideration of degradation extent in binary units can help us capture some important causal effects that may not be addressed by multiple linear regressions, due to the linearity assumptions of this method. The use of binary logistic regression also allows us to apply more techniques for model performance assessment, thus making the result evaluation more comprehensive.

#### 3.2.1.2 Land degradation intensity

We also used two variables to represent the intensity of the land degradation: reduction of annual mean NDVI (variable *DEG_INTEN*) and intensity level of degradation (variable *DEG_INTEN_L*). The former variable is measured as the percentage of the mean NDVI in the base year (1982), and the latter variable is captured on a binary scale: minor rate of degradation if the NDVI decline is less than 10% over 25 years (i.e., < 0.5% annually) (*DEG_INTEN_L* = 0), and substantial degradation rate otherwise (*DEG_INTEN_L* = 1). This threshold was adapted from Oldeman et al. (1991) and Le et al. (2012b). The inferential statistical methods applied for the two variables were similar to the degradation extent variables (see Table 3.1).

Given the decline in the biomass productivity of the land used as a proxy for land degradation, the interpretation of the actual meaning of the indicator itself and its causes cannot be uniform over heterogeneous agro-ecological space (Vlek et al., 2010; Vogt et al., 2011). In order to avoid flaw indications and assumptions, causal analyses of land degradation using the proxy indicator were recommended per spatial strata, defined by climatic, demographic, and ecological and land-use conditions (Sommer et al., 2011; Vlek et al., 2010; Vogt et al., 2011). Because land use refers to ecosystem exploitation (Nachtergaele and Petri, 2008) and is conditioned by several anthropogenic factors that define the social and ecological contexts for interpreting causalities from statistical results, broad land-use classes have been recommended for stratifying causal analyses and interpretations of land degradation (Sommer et al., 2011). Therefore, we analyzed the causes of land degradation intensity (via linear and binary logistic regressions) for each major land-use type, i.e., degraded agricultural land (*N* = 336 pixels, Figure 3.1a), degraded forest land (*N* = 385 pixels, Figure 3.1b), and severely degraded areas (*N* = 245 pixels, Figure 3.1c).

### 3.2.2 Description of hypothesized explanatory variables

Based on a review of the literature regarding the common determinants of land degradation (Jorgenson, 2006; Jorgenson and Burns, 2007; Jorgenson and Kuykendall, 2008; Vlek et al., 2010) and the availability of data on the national scale, we examined a total of 16 variables within 3 main categories: environmental, demographic, and economic variables. Brief definitions, the direction of the hypothesized effects, and data sources of these variables are shown in Table 3.2.

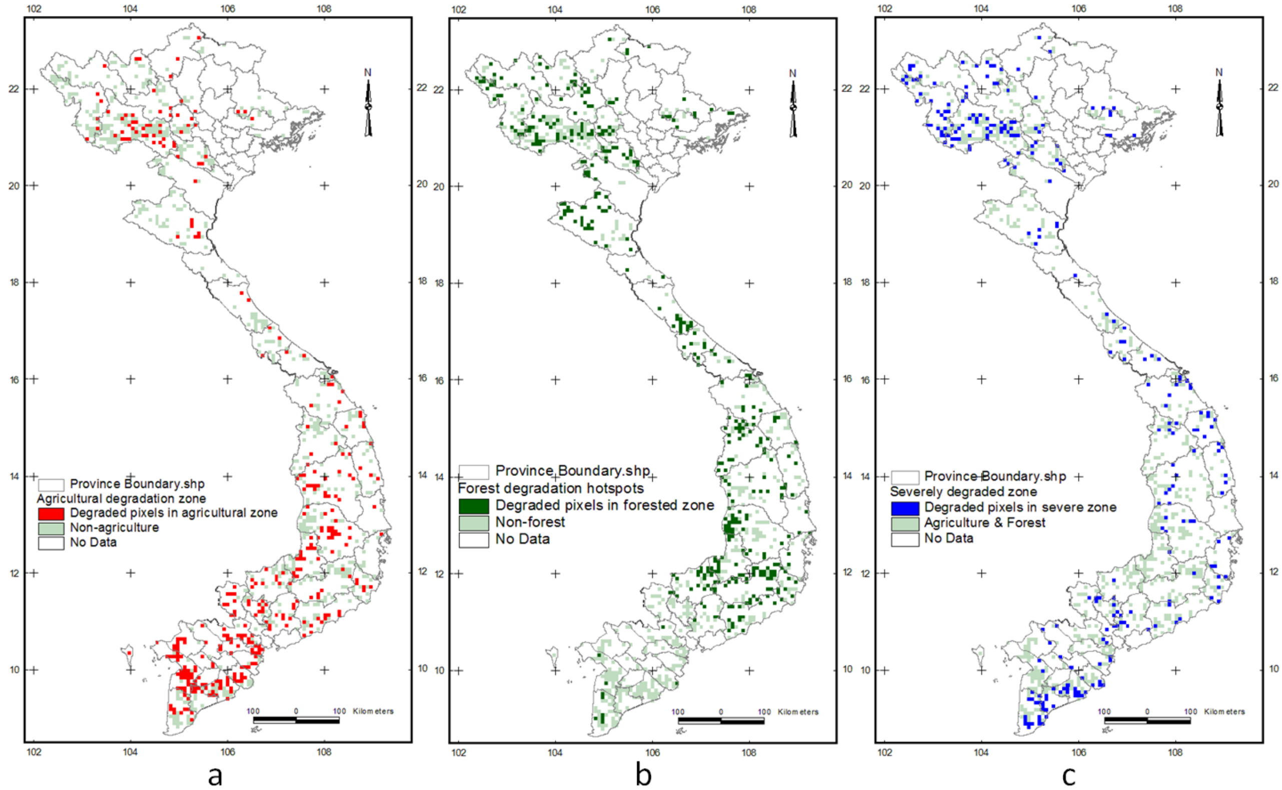


**Figure 3.1** Distribution of degraded pixels in (a) agricultural, (b) forested, and (c) severely degraded abandonment zones (Source: Vu et al., 2012a).

#### 3.2.2.1 Environmental variables

The potential effect of surface slope (SLOPE) on the biomass productivity of the land may be not the same direction over different land cover conditions. In agricultural land in gentle slope classes, surface slope is an important natural driver for soil erosion and/or landslides (De et al., 2008; Le, 2005; Sidle et al., 2006; Wezel et al., 2002b; Wischmeier, 1976), thus constraining crop productivity. However, a steep slope of forested land can be a natural constraint for people's access to exploiting forest products (e.g., selective logging) or to converting to permanent agricultural land, hence to help avoid forest clearance or degradation (Bader and Ruijten, 2008).

The soil combined constraint variable (SOILCONS) given by Fischer et al. (2002) consists of constraints for all the physical and chemical properties of soil to rain-fed crop production (i.e., soil depth, soil texture, soil quality, soil chemical, and soil drainage) that are very important for cultivation. This means that a high soil combined constraint theoretically inhibits the productivity of agricultural land. However, in forested areas, the variable can have a different effect. In a global review, forests on fertile soil in flat grounds have been reported to undergo high deforestation (Geist and Lambin, 2004), often associated with the conversion of this fertile forest soil to agricultural plantations.

**Table 3.2** Brief definitions and data sources of hypothesized explanatory variables for land productivity decline

| *Variable* | *Definition* | *Effect* | *Source* |
|---|---|---|---|
| *Environmental variables* | | | |
| SLOPE [a, c] | Surface slope (degree) | +/− | Shuttle Radar Topography Mission (SRTM) digital elevation model (USGS, 2004) |
| SOILCONS [a, c] | Soil combined quality constraint (3 classes: 1 = no/slight, 2 = moderate, 3 = severe/very severe) | + | Global Agro-ecological Assessment for Agriculture 2002 dataset (Fischer et al., 2002) |
| D_ROAD [a, c] | Distance to main road (km) | +/− | Calculated from National Base Map 1999 |
| D_TOWN [a, c] | Distance to town (km) | +/− | The same as those of D_ROAD |
| FOREST_NBH [a, c] | Forest abundance within the neighborhood (3 × 3 pixel size) of the considered location | − | Using the method of Verburg et al. (2004). Data taken from Global Land Cover 2000 (Stibig et al., 2000), and Vietnam Land Use Map 2005 (MoNRE, 2005) |
| AGR_NBH [a] | Agricultural abundance within the neighborhood | + | The same as those of FOREST_NBH |
| *Demographic variables* | | | |
| POP_DEN [b, c] | Population density (persons/km$^2$) | +/− | Vietnam Statistical Year Book 1995–2006 (VSYB 1995–2006) |
| POPDEN_CHG [b, c] | Change in population density (1995-2006) | +/− | Calculated from VSYB 1995–2006 |
| URBPOP_GR [b, c] | Annual urban population growth rate (1995 -2006) (%) | + | Calculated from VSYB 1995–2006 |
| RURPOP_GR [b, c] | Annual rural population growth rate from 1995 to 2006 (%) | + | Calculated from VSYB 1995–2006 |
| *Economic variables* | | | |
| POVERTY [b, c] | Poverty index | +/− | Minot et al. (2006) |
| GR_GDPCAP [b, c] | Mean growth rate of annual GDP per capita from 1995 to 2006 (%) | +/− | Calculated from VSYB 1995–2006 |
| APRD_CAP [b, c] | Mean annual agricultural gross product per capita (1995–2006) (1000 VND) | +/− | Calculated from VSYB 1995–2006 |
| GR_APRDCAP [b, c] | Annual growth rate of agricultural gross product per capita (1995–2006) (%) | +/− | Calculated from VSYB 1995–2006 |
| GR_AREACRP [b] | Annual growth rate of area of main crops [d] (1995–2006) (%) | + | Calculated from VSYB 1995–2006 |
| GR_CEREALYLD [b] | Annual growth rate of cereal crop yield (1995–2006) (%) | − | Calculated from VSYB 1995–2006 |

[a] Source data are pixel-explicit

[b] Source data are provincially explicit

[c] Variable used for district-based regression analysis. For soil combined constraint, the district-based median value was computed instead of the mean value

[d] Main crops include rice, maize, sweet potato, cassava, sugarcane, peanut, and soybean

Distances to main road (D_ROAD) or town (D_TOWN) represents transactional (or accessing) costs to the markets of both farming outputs (e.g., foods or woods) and inputs (e.g., fertilizers or pesticides). However, there is no consistent relationship between access to market and land degradation. Land users in areas with good market access may have more incentive to invest in good land management practices help mitigate land degradation as they clearly see the monetary benefits of the investments (Pender et al., 2006; Tiffen et al., 1994; Von Braun et al., 2012). However, in some cases, good market access can increase the opportunity cost of labor (e.g. better benefits with investments on alternative livelihood opportunities compared to attempts on improving land quality for agricultural production) that discourages land-users to adopt labor-intensive conservation farming (Scherr and Hazell, 1994; Von Braun et al., 2012).

The abundance of forest within the neighborhood of the considered location (FOREST_NBH) can support tree regeneration in fallowed or abandoned fields by providing sources of dispersed seeds or reducing the risk of soil erosion (FORRU, 2008). Thus, we hypothesized that this variable would have a negative effect on biomass productivity decline, especially on abandoned or fallowed sites. In contrast, an abundance of intensified cropland (e.g., paddy rice or cash crops) within the neighborhood (AGR_NBH) can accelerate the diffusion of agricultural intensification practices in less intensified farmland (Lambin and Meyfroidt, 2011). Therefore, we hypothesized that this variable is positive relationship to land degradation.

#### 3.2.2.2 Demographic variables

Population dynamics are often recognized as a prime underlying cause of land degradation or improvement (Müller and Zeller, 2002). However, the direction of the effect depends on the conditions of land use and the associated human communities. Indeed, the relationship between population growth and natural resource degradation was a debate between Malthusian and Boserup’s school of thought in the 1960s. In a closed society, an increase in population density would increase the demand for food, and this would act as an incentive to change agrarian technology to produce more food. Therefore, population growth can spark innovators who will solve land scarcity problems (Boserup, 1965; Marquette, 1997). However, population pressure in mountainous areas ensures that the extensive crop-fallow rotation cropping systems are no longer sustainable. Land pressure caused by both population growth and forest protection programs (that expel shifting cultivation activities from forest or woodlands) limit land areas for shifting cultivation practices. To ensure minimal household’s food demand upland cultivators have to shorten or cancel the fallow period, causing nutrient mining and soil erosion problems, in turn, hampering crop productivity (Jamieson et al., 1998; Le, 2005).

Analyses across less developed countries in the tropics have found that the growth rate of the urban population (URBPOP_GR) exerts “tele-effects” (i.e., effects taken over a far distance) on deforestation in remote areas (Angelsen, 1996; DeFries et al., 2010; Douglas, 2006; Geist and Lambin, 2004; Jorgenson, 2006; Jorgenson and Burns, 2007). However, it is still unclear if the effect remains the same within a country, as in our case. The growth rate of a rural population (RURPOP_GR) in a poorly managed forest land also increases the possibility of slash-and-burn and selective logging activities that cause deforestation or forest degradation.

#### 3.2.2.3 Economic variables

Poverty rate (POVERTY) is considered to be an underlying factor of land degradation (von Braun et al., 2012). Scherr (2000) and Barbier (1997) argued that there is often a downward spiral between poverty and land degradation in developing countries: poverty impedes farmers' ability to control land degradation, and land degradation, in turn, causes more livelihood problems. However, in some cases, if the poor depend heavily on land-based production, and market conditions allow the poor to allocate resources efficiently, they can have a strong incentive to invest their limited capital into preventing or mitigating land degradation (Nkonya et al., 2008). In this study, the poverty variable is defined as the proportion of the population living in households whose per capita expenditure is below the poverty line (i.e., the income level at one USD/person/day) (Minot et al., 2006b).

The annual growth rate of the gross domestic product (GDP) per capita (GR_GDPCAP) reflects the economic development in the considered district, which is often an important underlying factor in land degradation or improvement. However, there may be no defined answer whether this variable affects positively or negatively to land degradation. In less developed countries in the tropics, the rapid GDP growth mainly found in urban areas triggers deforestation in rural or remote areas, reflecting a "tele-effect" through accelerated flows of forest products from remote forests to consumers in cities (Cardille and Bennett, 2010; DeFries et al., 2010; Jorgenson and Burns, 2007). However, rapid economic growth in urban areas demands more food that often creates greater economic incentive for farmers to intensify their crop production, such as the cases in East Asian flood plains (Ali, 2002; Bo et al., 2003a; Hossain and Singh, 2000; Thuy et al., 2002). More specifically, the main production component of economic growth, i.e., industry or agriculture, is important for understanding the economic driver of land degradation or improvement. Agriculture-based growth—indicated by an increase in the annual agricultural gross product per capita (APRD_CAP) and annual growth rate of the agricultural gross product per capita (GR_APRDCP)—can trigger market-oriented intensive agricultural systems in suitable areas or extend more unsustainable agriculture on hill slopes at the same time. Thus, the effects of these two variables on land degradation are not clear.

The annual growth rate of the area of main crops (GR_AREACRP) and annual growth rate of cereal crop yield (GR_CEREALYLD) represent trends in agricultural production that can cause or mitigate land degradation in mountainous provinces with high forest coverage. The expansion of agricultural land is often associated with the conversion of forest or productive vegetation areas that cause biomass losses or increase soil erosion on slope lands. The GR_AREACRP variable was, therefore, hypothesized to cause more land degradation. The increase in provincial crop yield actually originated from some limited areas of agricultural intensification. The agricultural intensification in these areas may extract rural labors and harnessing food insecurity problems, thereby reduce time availability or need for forest exploitation (Godoy, 2001). Thus, the variable GR_CEREALYLD was expected to mitigate the degradation of forest land.

### 3.2.3 Evaluation of statistical analysis results

#### 3.2.3.1 Multicollinearity

High multicollinearity (i.e., strong linear relationship among two or more explanatory variables) can cause misleading regression analyses results. Before conducting the regression analyses, we tested for the multicollinearity of all explanatory variables using variance inflation factors (VIF) and tolerance values (1-$R^2$). There will be collinearity problems if the VIF values are greater than 5 and the tolerance values are less than 0.2 (DeFries et al., 2010).

#### 3.2.3.2 Spatial autocorrelation

Spatial autocorrelation, i.e., the observed value of a variable at one locality is independent of the values of the variable at neighboring localities, may be a problem for the pixel-based-regression analyses. Potential spatial autocorrelation in the variables of the pixel-based regressions should be compensated because the following features of our data integration:

- Large pixel size ensures relatively large distance (8 km) between the two nearest data points (i.e. the centres of the two adjacent pixels). This is much longer than the distance of 200 m set for minimizing spatial dependence in a precedent study in Central Vietnam (Müller and Munroe, 2005). The 8-km spacing in our data allows us to apply standard regression techniques (Anselin, 2001).
- To capture the influence of surrounding land-use and infrastructure conditions on the degradation variables, we include many variables such as spatial lag (8 km) slope (SLOPE), distances to road (D_ROAD) and town (D_TOWN), forest and agricultural abundance within a neighborhood of 3 × 3 pixels (FOREST_NBH and AGR_NBH). This is similarly to the way of addressing spatial dependency done by Munroe et al. (2002), Nelson et al. (2001) and Müller and Munroe (2005).

Both the large spacing and the uses of spatial lag variables help to reduce spatial autocorrelation although they do not totally eliminate it (De Pinto and Nelson, 2002; Müller and Munroe, 2005).

For the district-driven socio-economic variables, the problem is that the data are the same for all degraded pixels within a district. To test to what extent the spatial autocorrelation in these data may have adverse influences on the result, we calculated the Moran's *I* indices for these variables. The significance of this spatial autocorrelation index was evaluated by both the *Z*-score and the *p*-value (Moran, 1950). In general, a value of Moran's index ranges from −1 (perfect dispersion) to +1 (perfect clustered). A zero value indicates a random spatial pattern (no autocorrelation). *Z*-score values greater than 1.96 or smaller than −1.96 indicate significant spatial autocorrelation of the variable at 95% level.

#### 3.2.3.3 Model performance

For multiple linear regressions, our evaluation of statistical inference included (1) examining the overall significance of the regression model using *F*-statistics, (2) measuring the model's goodness-of-fit using *adjusted*-$R^2$, and (3) testing the statistical significance of partial causal effects by examining *p*-values. According to Greene (Greene, 2012), for a large cross-sectional data panel such as those used in this study, $R^2$ values of around 0.5 and 0.3 should indicate a good and not bad model performance, respectively.

Our performance evaluation of binary logistic regressions included (1) a chi-squared test for the overall statistical significance of the regression model, (2) the probabilities of correct prediction, and (3) receiver operating characteristic (ROC) statistics. Although some pseudo-$R^2$ in binary logistic regression mimics the widely used $R^2$ in linear regression, there are no agreed benchmark values of the pseudo-$R^2$ parameters for answering if the model performance is acceptable. Alternatively, we measured the goodness-of-fit of the model using receiver operating characteristic (ROC) statistics, as recommended by several experts in binary logistic regressions (Hosmer and Lemeshow, 2000; LaValley, 2008; Pepe et al., 2004). The ROC curve depicts the model sensitivity (True Positive Fraction) and model specificity (True Negative Fraction) over all possible cut-off points. The *area under the ROC curve* (theoretically ranging from 0.5 and 1.0) was used as the basis for evaluating model performance. If the area value is significantly ($p$ < 0.05) higher than 0.5, then the model predicts the output better than chance. Area values of 0.7–0.8 show acceptable model performance, values of 0.8–0.9 demonstrate excellent performance, and values greater than 0.9 indicate an outstanding performance (Hosmer and Lemeshow, 2000).

## 3.3 Results

The tests for multicollinearity showed that all VIF and tolerance values of all explanatory variables were less than 5 and greater than 0.2, respectively (Table S3.1). This indicates that there is no presence of multicollinearity between explanatory variables. The auto-correlation tests for district-driven demographic and economic variables show that spatial autocorrelation is the case with variables POVERTY, POP_DEN and APRD_CAP, calling into some cautions when interpreting the effects of these variables in the regressions. The Moran' *I* indexes of the remaining variables are nearly zero and *Z*-scores were in between -1.96 to 1.96 at almost tested threshold distances, indicating no serious spatial dependency for the regression analyses (Table S3.2).

### 3.3.1 Determinants of land degradation extent

The results of the multi-linear regression (MLR) model for degradation extent (DEG_SHARE) and binary logistic regression (bi-logit) for degradation extent level (DEG_SHARE_L) are reported in Table 3.3. An *F*-test indicated that the MLR model was statistically significant at the 0.1% level. However, the model was not strong in its prediction power ($R^2$ = 0.19). The Hosmer and Lemeshow test for the bi-logit model resulted in a *p*-value of 0.69 (> 0.05) that shows no statistically significant difference between the predicted degradation extent level and the observed data, meaning a good fit of the model to the data. The calculated area under the ROC curve was 0.683 (> 0.5), indicating that the model is a better predictor of the output than chance.

The environmental variables having significant effects on the spatial extent of land degradation included slope (SLOPE), soil combined constraint (SOILCONS), and distance to a road (D_ROAD). The affecting directions of these variables were as expected. The districts with significantly spreading rate of land degradation (i.e. more than 20%) were likely to have higher slope. In contrast, the more soil constraint and further distance to a road increased land degradation extent. Increase in population density (POP_DEN) and especially rural population growth rate (RURPOP_GR) affected significantly the extent of land degradation and showed the expected signs. The positive relationship of these demographic variables implies that area of land degradation was likely to increase by high population pressure. Regarding economic development variables, higher annual agricultural gross product per capita (APRD_CAP) led to wider degradation. However, the increase in the annual growth rate of the agricultural gross product per capita (GR_APRDCAP) has reduced the expansion of degraded area.

**Table 3.3** Results of regression analyses for identifying determinants of the spatial extent of land productivity decline (DEG_SHARE) and severe spreading of degradation (DEG_SHARE_L)

| Variable | Multiple linear regression for identifying determinants of DEG_SHARE | | Binary logistic regression for identifying determinants of DEG_SHARE_L | |
|---|---|---|---|---|
| | Estimated β coefficient | p-value | Estimated β coefficient | p-value |
| SLOPE | −0.264 | 0.236 | **−0.048*** | **0.054** |
| SOILCONS | **4.222**** | **0.028** | 0.299 | 0.155 |
| D_ROAD | 0.327 | 0.173 | **0.045*** | **0.078** |
| FOREST_NBH | −0.045 | 0.681 | 0.000 | 0.973 |
| POP_DEN | **0.012***** | **0.000** | **0.001**** | **0.030** |
| POPDEN_CHG | 0.108 | 0.281 | 0.009 | 0.388 |
| URBPOP_GR | −0.633 | 0.218 | −0.065 | 0.280 |
| RURPOP_GR | **2.045**** | **0.017** | **0.186**** | **0.045** |
| POVERTY | 7.522 | 0.316 | 0.645 | 0.422 |
| GR_GDPCAP | −0.003 | 0.989 | 0.023 | 0.350 |
| APRD_CAP | **0.004**** | **0.031** | 0.000 | 0.255 |
| GR_APRDCAP | **−0.984**** | **0.048** | −0.047 | 0.370 |
| Intercept | 5.711 | 0.448 | −2.217 | 0.011 |
| Model performance | *F*-test: $F = 7.108$, $df = 12$, $p < 0.001$<br>Goodness-of-fit: $R = 0.44$, $R^2 = 0.19$, adjusted-$R^2 = 0.16$ | | Hosmer and Lemeshow test: chi-square = 5.58, $df = 8$, $p = 0.69$<br>Overall corrected prediction: 64.7%<br>Area under ROC = 0.683 ($p < 0.001$) | |

*, **, ***: Statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$) and 99% ($p < 0.01$), respectively.

## 3.3.2 Determinants of land degradation intensity

### 3.3.2.1 Agricultural zone

On the aspect of the intensity of land degradation, the results of the regression analyses for identifying the determinants of the intensity of productivity decline (*DEG_INTEN*) and severe intensity of degradation (*DEG_INTEN_L*) in the agricultural zone are presented in Table 3.4. For the MRL, the result of the F-test showed that the model was statistically significant at the 0.1% level. The goodness of fit of the MRL model was low ($R^2 = 0.22$). For the bi-logit regression, the *p*-value of 0.34 from Hosmer and Lemeshow's test showed that there was no statistically significant difference between the observed degradation intensity level and the predicted data, meaning a good fit of the model. The area under the ROC curve was 0.75, demonstrating the acceptable performance of the model for identifying the determinants of land degradation intensity in the agricultural zone.

The results present in Table 3.4 indicated that there were no environmental variables significantly affecting the intensity of land degradation in the agricultural zone. For demographic variables, an increase in the total population density (POPDEN_CHG) and growth rate of the rural population (RURPOP_GR) significantly reduce land degradation per pixel. Three of the four selected economic variables (GR_GDPCAP, APRD_CAP, and GR_APRDCAP) showed significant effects on land degradation intensity in the agricultural zone (Table 3.4). Districts with higher annual growth rate of GDP per capita (GR_GDPCAP) have less degradation intensity. Similar to its effect on degradation extent, a higher annual agricultural gross product per capita (APRD_CAP) was likely to increase land degradation intensity, while the annual growth rate of agricultural production per capita (GR_APRDCAP) negatively influenced land degradation per pixel.

**Table 3.4** Results of regression analyses for identifying determinants of the intensity of productivity decline (DEG_INTEN) and severe intensity of degradation (DEG_INTEN_L) in agricultural zone

| Variable | Multiple linear regression for identifying determinants of DEG_INTEN | | Binary logistic regression for identifying determinants of DEG_INTEN_L | |
|---|---|---|---|---|
| | Estimated β coefficient | p-value | Estimated β coefficient | p-value |
| SLOPE | −0.03 | 0.677 | −0.006 | 0.859 |
| SOILCONS | 0.494 | 0.438 | 0.112 | 0.664 |
| D_ROAD | −0.038 | 0.495 | −0.016 | 0.465 |
| AGR_NBH | −0.03 | 0.152 | −0.002 | 0.810 |
| POP_DEN | 0.001 | 0.391 | 0.000 | 0.535 |
| POPDEN_CHG | **−0.105*** | **0.001** | **−0.025 ** | **0.042** |
| URBPOP_GR | −-0.211 | 0.208 | −0.083 | 0.217 |
| RURPOP_GR | **−0.68*** | **0.004** | **−0.299** | **0.010** |
| POVERTY | 2.397 | 0.251 | 1.058 | 0.228 |
| GR_GDPCAP | **−0.113*** | **0.086** | **−0.052*** | **0.057** |
| APRD_CAP | **0.002*** | **0.005** | **0.000** | **0.044** |
| GR_APRDCAP | **−0.732*** | **0.000** | **−0.196*** | **0.002** |
| Intercept | 14.238 | 0.000 | 0.649 | 0.567 |
| Model performance | F-test: $F$ = 7.45, $df$ = 12, $p$ < 0.001<br>Goodness-of-fit: $R$ = 0.46, $R^2$ = 0.22, *adjusted*-$R^2$ = 0.19 | | Hosmer and Lemeshow test: chi-square = 9.02, $df$ = 8, $p$ = 0.34<br>Overall corrected prediction: 73.2%<br>Area under ROC = 0.746 ($p$ < 0.001) | |

*, **, ***: Statistical significance at 90% ($p$ < 0.1), 95% ($p$ < 0.05) and 99% ($p$ < 0.01), respectively.

### 3.3.2.2 Forested zone

Similar analyses were done to identify the determinants of land degradation intensity in the forested zone, and the results are given in Table 3.5. The $F$-test showed that the MLR model was statistically significant at the 0.1% level. However, the model was not strong in its prediction power ($R^2$ = 0.14). Hosmer and Lemeshow's test for the bi-logit regression showed no statistically significant difference between the predicted degradation intensity level and the observed data ($p$-

value > 0.05), meaning a good fit of the model to the data. The area under the ROC curve was 0.72, confirming the acceptable performance of the bi-logit model.

**Table 3.5** Results of regression analyses for identifying determinants of the intensity of productivity decline (DEG_INTEN) and severe intensity of degradation (DEG_INTEN_L) in forested zone

| Variable | Multiple linear regression for identifying determinants of DEG_INTEN | | Binary logistic regression for identifying determinants of DEG_INTEN_L | |
|---|---|---|---|---|
| | Estimated β coefficient | p-value | Estimated β coefficient | p-value |
| SLOPE | −0.012 | 0.596 | 0.005 | 0.779 |
| SOILCONS | −0.252 | 0.421 | −0.046 | 0.862 |
| D_TOWN | −0.016 | 0.478 | −0.012 | 0.516 |
| POP_DEN | **0.005**** | **0.040** | **0.003*** | **0.075** |
| POPDEN_CHG | 0.006 | 0.740 | 0.013 | 0.346 |
| URBPOP_GR | −0.129 | 0.238 | −0.059 | 0.518 |
| RURPOP_GR | **0.416**** | **0.027** | 0.165 | 0.296 |
| POVERTY | 0.065 | 0.955 | −0.480 | 0.610 |
| GR_GDPCAP | −0.069 | 0.115 | −0.037 | 0.283 |
| APRD_CAP | **0.001**** | **0.039** | 0.000 | 0.780 |
| GR_APRDCAP | **−0.433***** | **0.000** | **−0.236***** | **0.002** |
| GR_AREACRP | 0.122 | 0.116 | 0.101 | 0.112 |
| GR_CEREALYLD | **−0.379***** | **0.000** | **−0.171**** | **0.026** |
| Intercept | 11.928 | 0.000 | 0.825 | 0.538 |
| Model performance | F-test:<br>$F = 4.52$, $df = 13$, $p < 0.001$<br>Goodness-of-fit:<br>$R = 0.37$, $R^2 = 0.14$, $adjusted\text{-}R^2 = 0.11$ | | Hosmer and Lemeshow test:<br>chi-square = 7.22, $df = 8$, $p = 0.51$<br>Overall corrected prediction: 82.6%<br>Area under ROC = 0.718 ($p < 0.001$) | |

*, **, ***: Statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$) and 99% ($p < 0.01$), respectively.

Similar to the agricultural zone, environmental variables had no significant effects on land degradation intensity in the forested zone. Population density (POP_DEN) and the growth rate of the rural population (RURPOP_GR) all have a significantly positive effect on the intensity of land degradation, implying that high population pressures are likely to increase land degradation intensity. Three economic variables significantly affected the intensity of land degradation in the forested zone, including APRD_CAP (positive), GR_APRDCAP, and GR_CEREALYLD (both negative).

#### 3.3.2.3 Severely degraded zone

The performance of the MLR model for the severely degraded zone was not bad compared to the common standard of a cross-section regression (i.e., *F*-test was significant at $p < 0.01$, $R^2 = 0.29$). The bi-logit model had a good fit with the observed data (the Hosmer and Lemeshow test had a *p*-value of 0.8) and acceptable prediction performance (the area under the ROC curve was 0.79) (Table 3.6).

**Table 3.6**. Results of regression analyses for identifying determinants of the intensity of productivity decline (DEG_INTEN) and severe intensity of degradation (DEG_INTEN_L) in severely degraded abandonment zone

| Variable | Multiple linear regression for identifying determinants of DEG_INTEN | | Binary logistic regression for identifying determinants of DEG_INTEN_L | |
|---|---|---|---|---|
| | Estimated β coefficient | p-value | Estimated β coefficient | p-value |
| SLOPE | −0.042 | 0.441 | −0.023 | 0.355 |
| SOILCONS | −0.239 | 0.807 | 0.203 | 0.618 |
| D_ROAD | −0.04 | 0.397 | **−0.046*** | **0.060** |
| FOREST_NBH | **−0.124***** | **0.001** | −0.001 | 0.121 |
| POP_DEN | −0.003 | 0.129 | −0.009 | 0.568 |
| POPDEN_CHG | −0.055 | 0.132 | −0.037 | 0.671 |
| URBPOP_GR | **−0.379*** | **0.069** | **−0.333***** | **0.006** |
| RURPOP_GR | **−0.686**** | **0.014** | 0.327 | 0.759 |
| POVERTY | −0.049 | 0.985 | 0.006 | 0.914 |
| GR_GDPCAP | −0.106 | 0.415 | 0.000 | 0.263 |
| APRD_CAP | **0.001*** | **0.086** | −0.078 | 0.324 |
| GR_APRDCAP | **−0.345*** | **0.076** | **−0.048***** | **0.007** |
| Intercept | 18.957 | 0.000 | 0.678 | 0.697 |
| Model performance | F-test:<br>$F = 7.99$, $df = 12$, $p < 0.001$<br>Goodness-of-fit:<br>$R = 0.54$, $R^2 = 0.29$, $adjusted\text{-}R^2 = 0.27$ | | Hosmer and Lemeshow test:<br>chi-square = 4.64, $df = 8$, $p = 0.80$<br>Overall corrected prediction: 77.6%<br>Area under ROC = 0.790 ($p < 0.001$) | |

*, **, ***: Statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$) and 99% ($p < 0.01$), respectively.

The abundance of forest cover within the neighborhood of the considered location (FOREST_NBH) and further distance to a road (D_ROAD) affected negatively land degradation. The affecting direction of FOREST_NBH is as expected. In contrast to the hypothesized effects, the growth rate of the urban population (URBPOP_GR) and rural population (RURPOP_GR) had negative effects on degradation. It means the increases of these demographic variables were likely to decrease land degradation intensity. The economic development variables have significant effects on the degradation intensity of abandoned and degraded land including the annual agricultural gross product per capita (APRD_CAP) (positive) and annual growth rate of APRD_CAP (GR_APRDCAP) (negative).

### 3.3.3 Cross comparison of causal patterns for different degradation categories

In order to compare the patterns of the determination of land degradation extent and intensity in different land use zones, we used standardized weight coefficients of significant variables as shown in Figure 3.2. The figure highlights the most important causes of land degradation. Agricultural gross product per capita (APRD_CAP) and annual growth rate of APRD_CAP (GR_APRDCAP) have consistent effects on the four categories of land degradation. However, the affecting directions of these two variables are opposite

Population density (POP_DEN) had a major impact on overall land degradation extent, but not so with land degradation density per pixel. This is understandable, as a large share of Vietnam, located in a monsoon tropical climate zone, is mountainous, making it fragile and, hence, with a low carrying capacity for hosting a human population (Marten, 2001; Vien, 2003). Moreover, an increase in population density (POPDEN_CHG) is a specific cause of less land degradation in agricultural zones, mainly in the crowded deltas of the Red and Mekong Rivers. The growth rate of a rural population (RURPOP_GR) is commonly a significant cause of degradation, but shows in different affecting directions, depending on the aspect of degradation (extent or intensity) and considered land use strata (agriculture, forest, or abandoned, unproductive land).

Neighboring forest has shown its importance for reducing land degradation intensity in abandoned, unproductive land, while it is not the case for land degradation elsewhere. The soil combined constraint increases the severity of the degradation extent.

.

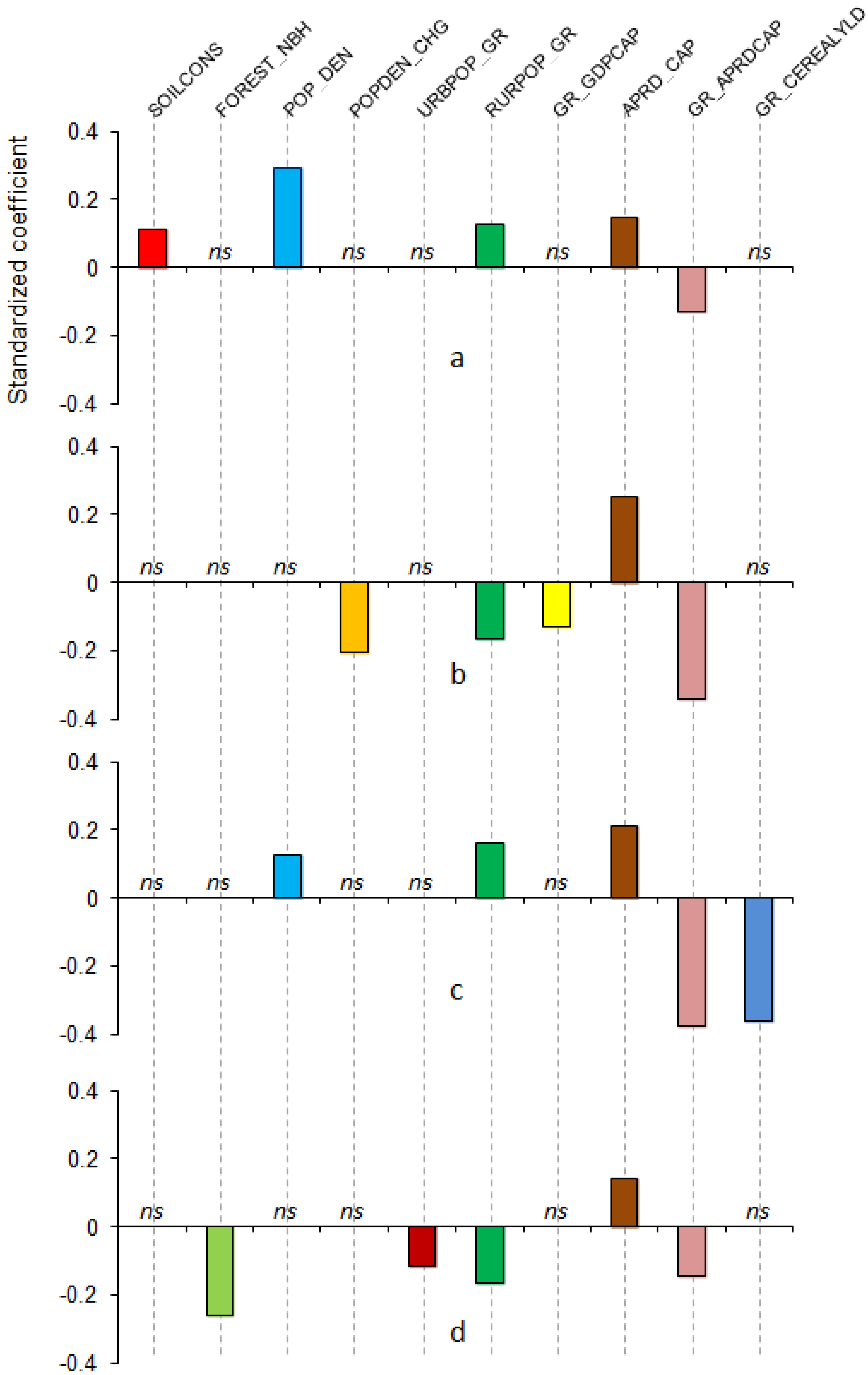


**Figure 3.2** Standardized weight coefficients of variables that affect significantly (a) the extent of degraded land in a district (DEG_SHARE_L), the intensity of degradation on a pixel (DEG_INTEN_L) in (b) agricultural zones, (c) forested zones, and (d) severely degraded zones. *Note*: Only significant variables are presented; *ns* = no significant effect.

## 3.4 Discussion

### 3.4.1 Contextualization of the empirical findings in the related previous studies

Through considering a wide range of socio-economic and biophysical factors, we highlighted that the effect of environmental factors on land degradation is not likely to be common in all land-use zones as compared to economic and demographic development variables. In the two important land-use areas (agricultural and forested zones), not all environmental variables significantly affected land degradation intensity, while agricultural production growth had significant effects in all land-use zones. Population density also had the most important effect on land degradation extent. The results are consistent with the study of Grepperud (1996), who pointed out that human activities constitute the primary cause of soil degradation compared to the weak effects of environmental variables, such as soil properties, slope, and rain intensity. However, our results also imply that the effects such as the richness of surrounding forest cover become important for natural restoration in abandoned degraded land, as stated by FORRU (2008).

Our results revealed that population pressure is an important factor affecting land degradation, but understanding its causality requires accurate contextualization. Previous reviews argued that there has been no consistent relationship between population growth and land degradation, but they did not clarify the contexts and related causalities (Scherr et al., 1995; Von Braun et al., 2012). The positive effects of population growth on land degradation extent and degradation in mountain forest areas (Figure 3.2a and c) suggest that population pressure will be an issue in areas with (1) low carrying capacity, such as tropical mountains and hill sides, and (2) frontier or extensive agrarian communities. Sloped tropical forest lands are highly fragile and have much lower carrying capacity for hosting a forest/agriculture-based population compared to other lands (Jamieson et al., 1998). Rural population growth increases the likelihood that forested regions will be transformed, cut, or burned for extractive processes, or extensive agricultural production (Jorgenson and Burns, 2007; Rudel, 1989; Rudel and Roper, 1997). In mountainous area with shifting cultivation, increase population pressure (due to rural population growth combined with government policies restricting farmers' access to protected forest lands) also forces mountain farmers to shorten or cancel fallow periods, leading to rapid soil degradation due to soil erosion and nutrient mining. Our results are also consistent with the findings of Grepperud (1996) and Bai et al. (2008b), whose studies were carried out on large scales (i.e., all of Ethiopia or global) and in which marginal areas with extensive use activities occupy a large share of the total considered area. The negative effect of population growth in intensive cultivation areas in the Red River and Mekong deltas of Vietnam[4] (Figure 3.2b) suggests that Boserup's hypothesis (Boserup, 1965) is likely valid in crowded cultivation areas in Vietnam's lowlands. Further, it is likely that increased population pressure in the conditions of improved market access and extension services have motivated farmers to be innovative and invest in different forms of intensified farming practices that can bring about crop production on infertile land.

[4] At the resolution observed in this study (64 km$^2$ pixel), the captured agricultural areas are mainly in intensified cultivation zones in Vietnam's Red River and Mekong River deltas.

### 3.4.2 New features of the used approach

We analyzed the causes of land degradation considering the two different dimensions of the severity of the phenomenon, namely, degradation (1) extent and (2) intensity, as advocated by Oldeman et al. (1991) in the GLASOD study. However, the GLASOD and some follow-up work (e.g., Ayoub, 1998) identified a few degradation causes based on expert opinions rather than on objective inferences, as showed by the presented work. Some previous studies tried to correlate socio-economic factors, such as population density, land use, and poverty, to either the degree of biomass productivity decline (Bai et al., 2008b) or the extent of land degradation (Vlek et al., 2008, 2010). However, these studies were limited to the identification of a correlative pattern between degradation extent and social–ecological factors, which are not necessarity causal patterns, as the authors did not use inferential statistics. Previous causal analyses of land degradation using inferential statistics considered only the intensity of greenness reduction (Nkonya et al., 2011a) or the spatial extent of degradation (DeFries et al., 2010; Jorgenson and Burns, 2007; Reddy, 2003) rather than a dual consideration of the two specific facets of land degradation. With the presented study, we illustrated that the causation patterns for degradation extent can be remarkably different from those of degradation intensity, and the differentiation of the two facets of land degradation can make the causal analysis more *specific* and *clearer* (i.e., with less confounding factors) regarding the interpretation of the causalities underlying the inferred statistical relationships.

By identifying the degradation causes for major *separate land-use types*, the presented study is an exemplary case for clarifying the land use context, and thereby supports the improvement of degradation cause assessments. There are several reasons for conducting better contextualizing causal analyses of land degradation on large scales (e.g., national, regional, or global scales). Since land degradation indicators on these large scales (the dependent variables of causal analyses) are often the decreasing trends of Net Primary Productivity having different meanings in different social–ecological contexts, an adequate understanding of land degradation causes can be achieved only if the context is clarified. Nkonya et al. (2011a) measured the statistical effects of demographic and economic developments on change in vegetation greeness in East Asia, but due to the absence of a clear context, they noticed that no causalities could be drawn from the regression results. Although several reviews or meta studies have recently recommended that causal analyses of land degradation on large scales should be carried out within defined strata of land-use regimes to increase the correctness and comprehensiveness of the results (Reynolds et al., 2011; Sommer et al., 2011; Vlek et al., 2008; Vlek et al., 2010; Vogt et al., 2011), we have yet to find any such published work. Our results demonstrate that the contextualization of degradation cause analyses using the three broad land-use types helped us interpret the plausible causalities underlying the detected statistical relationship.

Our study included three categories of variables covering the important sectors related to land degradation. While only economic and demographic variables have commonly been used for identifying the determinants of land degradation and deforestation at the national or international levels (Bai et al., 2008b; DeFries et al., 2010; Jorgenson and Burns, 2007; Nkonya et al., 2011a), our study included other variables, such as slope, soil constraints, biophysical and institutional accessibilities, and abundance of forest and agriculture within the neighborhood of the considered locations, which were not used in previous studies. We showed that these variables were important in determining land degradation extent and intensity (Figure 3.2); thus, they should not be overlooked in land degradation cause assessments.

The presented study used two common inferential statistical methods (MLR and bi-logit regression) in a complementary way to improve the detect ability and credibility of the causal analysis using large cross-section datasets. As each regression method is common in inferential statistics, there would be been no methodological insight if only one of the techniques are used alone. As we showed, these two techniques can be used in a complementary way to overcome their common limitations. MLR can utilize the continuous scale of dependent variables, but it is weak in its goodness-of-fit performance due to its linearity assumptions. Although bi-logit regression is limited to the binary scale of degradation variables, it can detect the effects of variables having no strong Pearson correlation with the continuous variables of degradation, and the model can have a better prediction performance than those using MRL. Moreover, the large share of factors having significant effects in both models indicates the good convergence validity (Scholz and Tietje, 2002) of our results.

### 3.4.3 Implication for sustainable land management policy

In Vietnam, combating land degradation have been recognized and institutionalized for the last three decades; however so far the related policies have had certain shortcomings that still need to be systematically improved (NAP, 2002). The clarification of the causation pattern for each land-use zone from the present study can provide new insight for national policies on combating land degradation. First, current Vietnamese policies for combating land degradation have rather focused on protection and recovering of forest covers in the upland and mountain areas with a simplistic technological view, despite that the causes of land degradation act as a social–ecological conjuncture. The first large-scale reforestation program implemented for the 1992-1998 period – The 327 Program or “Regreening the barren hills program” – were also originated by a national perception of ecological degradation of the mountainous areas and its consequences on rural poverty (Lambin and Meyfroidt, 2010). The subsequent large-scale program – The 661 Program or the “Five million hectares reforestation program” – expected to increase the national forest coverage to 43% as the figure in 1942, and at the same time ensure timber production to support industrial activity (Clement and Amezaga, 2009). However, these programs have been carried out with simplistic view of technical forest rehabilitation or protection, without taking the social perspectives into account (Lambin and Meyfroidt, 2010; Meyfroidt and Lambin, 2009).

The causal pattern in forested areas here-identified suggests that certain social factors should be considered in formulating policy levers for mitigating land degradation in the Vietnam uplands. These includes measures for reducing migration into the Vietnamese uplands (Anh et al., 2003; Douglas, 2006; Jamieson et al., 1998) are critical for avoiding further degradation of the upland in the long term. Where the local population has already exceeded the mountain carrying capacity, the continuation of policy measures to support agricultural intensification in limited, suitable areas is recommended to compensate for the protection of hill slopes from shifting cultivation. The locations of these hotspots have been clearly identified in our companion paper (Vu et al., 2012a). Improved extension services and education are important for creating local incentive and innovation in sustainable intensification in the uplands. Given that the mountainous areas are highly fragile to the sizes of non-forest gaps, the large scale conversion of forest to agricultural land should be avoided.

Second, in the fertile main river deltas of Vietnam, the agricultural development policies aim at promoting food productivity for exportation and domestic food security with a limited blueprint. This includes intensification of rice-based agricultural land for increase crop productivity with a hope to compensate the decline of lowland agricultural areas due to urbanization; and integrate more livestock production (mainly pigs and poultry) for improving farmers' incomes and meat-preferred diet of a rapid growing economy (Bo et al., 2003a). This policy tendency has led to serious problems of water pollutions (Vu et al., 2012b; Vu et al., 2007), low nutrient use efficiency (Hossain and Singh, 2000) and economic vulnerability of the intensified farming systems (Bo et al., 2003a). Costs of these environmental impacts have not been aware and addressed by current agricultural land management policies in Vietnam.

The strong positive effect of gross agricultural product per capita on land degradation means that the agricultural development in Vietnam has not been ecologically efficient for the past 20 years, and that can hamper the nation's long-term food security. Given that agricultural intensification is crucial for ensuring the food security of the landless agrarian communities (Bo et al., 2003a), the development of new policy instruments to internalize the intensification's environmental externalities should be a priority in the future development of national policy for agriculture. Efforts in this direction require an evaluation of the environmental cost over the life cycles of agricultural products (Nemecek et al., 2011a; Nemecek et al., 2011b; Tuomisto et al., 2012; Williams et al., 2010), and based on that evaluation, new policies regarding payment for ecosystem services can be formulated. However, so far most life cycle assessments for agricultural systems have still been limited to the evaluation of the impact of production on biodiversity, fossil energy, and greenhouse gases, rather than land degradation. The aforementioned approach is currently absent in agricultural policy and planning in Vietnam. Therefore, the internalization of land degradation and water pollution in farming system evaluation and management policy is likely a fruitful research field.

Third, policies for combating land degradation in Vietnam have not taken into account the cross-sectors effects (e.g. the cause-effect relationship between processes in forested upland/mountain, and those in agricultural and urban zones) which are evidential in our results. In many cases, forest degradation in mountainous areas has been caused by not only the impacts of local drivers, but also by the increasing demand on timber products in the cities. Moreover, the effectiveness of the land management policies implemented on particular areas depends on the natural and socio-economic conditions of other neighboring regions. For instance, the land allocation policies are more successful in the lowlands than in the uplands, because the lowlands have many advantages for intensive agricultural production (e.g. labor resources, inputs and capital, and markets), which are lacking in the upland areas.

## 3.5 Conclusion

In this study, the biophysical and socio-economic factors were examined to determine the significant effects of them to both land degradation extent and intensity in deferent land-use zones. We found that land degradation is not caused by a single factor, but by an interaction between biophysical and socio-ecological components. The results indicate that land degradation is not very much due to selected natural variables, but mainly to demographic and economic variables. Whilst agricultural production growth showed strong and consistent effects on the considered aspects of land degradation, the demographic variables affected differently. Population density had a major impact on overall land degradation extent, but this was not so with land degradation intensity per pixel. Moreover, an increase in population density is a specific cause of less land degradation in agricultural zones, including mainly intensified areas in major river deltas. The rural population growth rate is commonly a significant cause of degradation, but it shows in different affecting directions, depending on the aspect of degradation (extent or intensity) and considered land use strata (agriculture, forest, or abandoned, unproductive land). A neighboring forest has also shown its importance for reducing land degradation intensity in abandoned, unproductive land, but this is not the case for degradation in other lands. Soil combined constraint increased the severity of degradation extent, but there is no evidence of the effect of this factor on land degradation intensity.

The study is an exemplary case that demonstrates that adequate problem faceting, social–ecological stratification, and complementary uses of common regression analyses can help arrive at sufficient detection and understanding social–ecological causes of a complex environmental phenomenon like land degradation at the national level. The concrete faceting of complex phenomena like land degradation allowed us combine the defined social–ecological contexts and contemporary hypotheses or theories in the field to clarify the likely causalities underlying the statistical relationships. The dependent variables considered in the study are spatial both degradation extent and degradation intensity in three different land-use zones (agriculture, forest and severely degraded abandonment). The considered explanatory variables are not only common economic and demographic drivers, but also bio-physical factors such as soil, terrain constraints and neighborhood land-use structures that are often neglected in many large-scale land degradation assessments. Instead of using a single inferential statistic technique, we used multi-linear regression and binary logistic regression in a complementary manner to increase the detect ability and credibility of the degradation cause analyses.

We realize that there are some limitations in the presented study that should be addressed in follow-up efforts. Most of the socio-economic data were province level data, as this was all that could be obtained from the national statistics. Even though they were aggregated in GIS format and nested with land degradation and other environmental data at 64 $km^2$ pixel resolution, the coarse resolution of the socio-economic data may have yielded some uncertainty in the results. As the causal patterns were drawn over the entire land-use zones across the country, the results were about general patterns rather than region-specific ones. Understanding region-specific patterns of land degradation requires the consideration of the data at finer levels. It is also interesting to understand how the causation patterns of productivity degradation were changing over different shorter periods. However, this work should be the subject of some follow-up studies as the causal analyses across multi periods demand longitudinal data of the hypothesized drivers whose collection is beyond the scope of this study.

## Appendix A. Supplementary materials

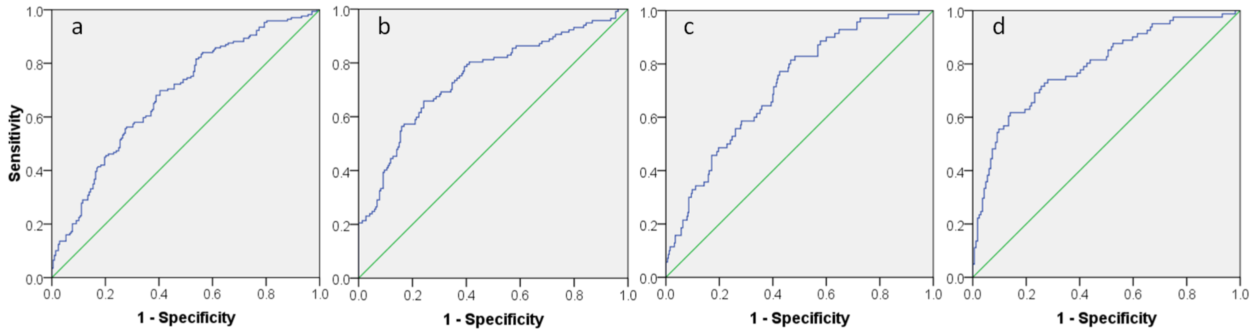


**Figure S3.1** ROC curves delineated for four binary logistic regressions for identifying determinants of (a) severe spreading of degradation in district (DEG_SHARE_L), and (b) severe intensity of degradation (DEG_INTEN_L) in agricultural zone, (c) in forested zone, (d) in severely degraded abandonment zone.

**Table S3.1** Multicollieartity diagnostics: Variance Inflation Factor (VIF) and tolerance values for variables used in linear regression a) for district dataset and b) for pixel dataset. VIF should be less than 0.5 and Tolerance values should be greater than 0.2 and to avoid multicollieartity.

a)

| Dependent Variable: DEG_SHARE | | |
|---|---|---|
| | Tolerance | VIF |
| SLOPE | 0.41 | 2.43 |
| ME_SOILCONS | 0.87 | 1.14 |
| D_ROAD | 0.74 | 1.35 |
| POP_DEN | 0.68 | 1.47 |
| POPDEN_CHG | 0.81 | 1.24 |
| URBPOP_GR | 0.86 | 1.16 |
| RURPOP_GR | 0.76 | 1.31 |
| POVERTY | 0.35 | 2.87 |
| GR_GDPCAP | 0.73 | 1.37 |
| APRD_CAP | 0.51 | 1.97 |
| GR_APRDCAP | 0.52 | 1.93 |
| FOR3_NBH | 0.43 | 2.35 |

b)

| Dependent Variable: ∆NDVI% | | |
|---|---|---|
| | Tolerance | VIF |
| SLOPE | 0.55 | 1.80 |
| SOIL_CONST | 0.86 | 1.17 |
| D_ROAD | 0.81 | 1.24 |
| POP_DEN | 0.56 | 1.77 |
| POPDEN_CHG | 0.71 | 1.41 |
| URBPOP_GR | 0.76 | 1.31 |
| RURPOP_GR | 0.69 | 1.44 |
| POVERTY | 0.42 | 2.38 |
| GR_GDPCAP | 0.57 | 1.75 |
| APRD_CAP | 0.51 | 1.97 |
| GR_APRDCAP | 0.53 | 1.89 |
| FOR3_NBH | 0.52 | 1.93 |

**Table S3.2** Spatial autocorrelation test for district-driven demographic and economic variables*. Moran'I index should be zero and Z-score should be smaller than 1.96 and greater than -1.96 to ensure random pattern (the pattern is neither clustered nor dispersed) of a variable.

| | Moran's *I* index | | | | | | *Z*-score | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Threshold distance / Variable | 2 | 4 | 6 | 8 | 10 | 12 | 2 | 4 | 6 | 8 | 10 | 12 |
| POPDEN | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 7.88 | 5.74 | 6.57 | 8.53 | 10.39 | 4.29 |
| POPDEN_CHG | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | -0.01 | 1.36 | 1.56 | 1.71 | 2.33 | 2.74 | 1.47 |
| URBAL_POP | -0.02 | -0.03 | -0.03 | -0.02 | -0.02 | -0.01 | 0.02 | -1.04 | -0.74 | -0.90 | -0.67 | 3.94 |
| RURAL_POP | 0.02 | 0.00 | -0.01 | -0.02 | -0.02 | -0.02 | 1.74 | 0.76 | 0.10 | -0.86 | -0.92 | -0.22 |
| POVERTY | 0.27 | 0.22 | 0.18 | 0.15 | 0.08 | 0.01 | 221.50 | 212.95 | 219.59 | 250.51 | 239.10 | 117.91 |
| GR_GDPCAP | -0.02 | -0.03 | -0.03 | -0.03 | -0.02 | -0.02 | -0.46 | -0.83 | -0.93 | -1.14 | -0.73 | 0.55 |
| APRD_CAP | 0.23 | 0.22 | 0.17 | 0.12 | 0.05 | 0.25 | 12.98 | 14.50 | 14.18 | 13.98 | 12.85 | 13.21 |
| GR_APRDCAP | 0.01 | -0.03 | -0.03 | -0.02 | -0.01 | -0.01 | 0.56 | -0.76 | -0.82 | -0.58 | 0.41 | 0.66 |
| GR_AREACRP | 0.00 | -0.03 | -0.02 | -0.03 | -0.02 | -0.02 | 0.97 | -0.68 | -0.30 | -1.29 | -0.94 | 0.46 |
| GR_CEREALYLD | 0.05 | 0.01 | 0.00 | 0.00 | 0.00 | -0.01 | 3.68 | 1.98 | 1.54 | 1.46 | 2.56 | 2.05 |

* Parameters selection for Global Moran' I test using ArcGIS toolbox: Conceptualization of spatial relationships= Zone of indifference; Distance Method= Euclidean distance; Standardization= Row; Distance band or Threshold distance = 2, 4, 6, ..., 12 decimal degrees (one degree of longitude at the equator equals to 111.321 km).

# 4. The importance of livelihood diversity in determining households' decisions on fertilizer use

## Abstract

Adopting an adequate nutrient management, including the use of water soluble mineral fertilizers and manure, is essential for smallholder's agriculture of tropical mountains to become sustainable. These agro-ecosystems are, however, extremely diverse and farmers have probably very different adoption behaviors. It is therefore of utmost importance to understand the social and ecological factors affecting the use of fertilizers and manures for designing policies that will leverage farmers' incentives to invest in sustainable nutrient use practices. The Yen Chau district of Son La province is considered as one of the most degraded and poorest regions in Vietnam and was studied as a test case. This paper aimed to identify (1) the main types of households and (2) the determinants of households' adoption of water soluble mineral fertilizers (e.g., urea and NPK compound) and manure uses. Using a stratified random sampling, we surveyed the natural, physical, human, social, financial assets, the quantity of NPK fertilizer used and the adoption of manure in 184 households. We defined six smallholder household types using Principal Component Analysis (PCA) and K-Means Cluster Analysis (K-CA). Regression analyses were used for inferring the effects of a wide range of variables on farmers' decisions about the use of mineral fertilizer and the adoption of manure. We found that the cause-effect relationships between the affecting factors and farmer decisions can vary over different household types. Household types with large household size but little farm land per capita were likely use more mineral fertilizers for maize and rice fields, while those have high labor force and raise a lot of more pigs tend to adopt use manure for rice field than the others. This implies that nutrient management policies need to be sensitive to specific livelihood types.

## 4.1 Introduction

Land degradation and food insecurity are interrelated major global issues (Lal et al., 2012; Von Braun and Gerber, 2012). Land degradation affects rural livelihoods as it reduces crop productivity that negatively impacts food security (Eswaran et al., 2001; Scherr and Yadav, 1996; Stocking and Murnaghan, 2001). At the same time, many factors of rural livelihood[5] constrain farmers' investments/efforts to recuperate degraded land for production (Nkonya et al., 2011b).

The northwest mountains of Vietnam provide a typical example of problems of land degradation and food insecurity. The region suffers from serious and extensive human-induced land degradation (UNCCD, 2006; Vu et al., 2012a; Vu et al., 2014b). Though food security has been improved in the flood plains, food shortage and poverty are still widespread in mountainous and hilly areas (Hoang et al., 2013; Phien and Siem, 1998). The constraints include the high ecological fragility of the sloping land, farmers' limited access to resources for agricultural production, lack of alternative forms of employment, education, and technology, and weak markets for both agricultural' inputs and outputs (Leisz et al., 2005; Minot et al., 2006b). Given these constraints farmers often expand their cultivated surfaces over the mountainous landscape, causing deforestation and increasing soil erosion (Lam et al., 2005; Wezel et al., 2002a). In the long term, the resulting environmental degradation reinforces food insecurity, farms' vulnerability to shocks or stresses, and rural poverty.

There were no or little external fertilizer inputs in Vietnam before the Era of Renovation (Bo, 2003). Continuous cultivation without or with too little fertilizer inputs caused negative soil nutrient balance, leading to decreased nutrient availability, decreased crop yields, and ultimately to soil degradation (Mutert, 1996). The intensification of rice production and of other cash crops from 1990 onwards was paralleled by a significant increase in mineral fertilizer use in Vietnam. The average amount of $N+P_2O_5+K_2O$ applied to crops in Vietnam increased from 55 kg/ha/year in1970 to 200 kg/ha/year in 2012 (Bo, 2013). Heffer (2013) estimates that 1250, 650 and 400 thousand metric tons of N, $P_2O_5$ and $K_2O$, respectively, had been applied as water soluble mineral fertilizers in Vietnam in 2011.

Despite the strong increase in fertilizer use in Vietnam nutrient depletion remains a big problem in northern mountains (Dung et al., 2008; Lam et al., 2005; Tuan et al., 2014). For instance, soil N content in basalt and schist-derived soils was reduced by half after 4 years of rice cultivation (Hung, 2001). Most upland soils have a low pH, and contain very little organic matter and available nutrient. (Bo et al., 2003).

Although agronomic knowledge and technologies for improved nutrient management are available (Bo, 2013; Dang, 2005; Frossard et al., 2009; Howeler and Phien, 2000; Mussgnug et al., 2006; Vanlauwe et al., 2010), these are not yet widely adopted in the northern mountains of Vietnam. The underlying question is how to formulate and implement policies that can leverage farmers' adoption of appropriate uses of mineral fertilizers and organic nutrient resources. We hypothesize that this requires an understanding of farmers' decisions on nutrient use. This understanding can be identified by analyzing the factors affecting their decisions. In mountainous regions, highly diverse social, economic, and ecological conditions determine farmers' livelihood options (Koerner and Ohsawa, 2005) and thus make the task challenging. For instance, social and

[5] A rural livelihood is defined as "the capabilities, assets and activities that rural people require for a means of living" (Carney, 1998)

cultural backgrounds are very heterogeneous: 31 of 54 ethnic groups of Vietnam live in the northern mountainous region with a high diversity in terms of languages, origins, religions and culture (Michaud et al., 2002; Vien, 2003). The farming systems in these areas are also diverse because of a wide range of agricultural activities (crop and livestock production, timber, and fishing) and non-agricultural activities (services, handcrafts, and tourism) (Vien, 2003).

Studies on factors influencing fertilizer use in smallholder farming systems were conducted in Asia (Adhikari, 2011; Aregay and Minjuan, 2012; Chouichom and Yamao, 2011; Paudel et al., 2009; Zhou et al., 2010), and in Africa (Akpan and Aya, 2009; Marenya and Barrett, 2007; Olayide et al., 2009; Waithaka et al., 2007). Although these studies identified causal effects of a wide range of biophysical factors (e.g., soil carbon content, slope and farm size) and socio-economic factors (e.g., household size, educational status, income level and land tenure) on fertilizer use, only few studies differentiated the affecting factors that are specific for different farmer groups in the study communities. In the study of determinants of the land-use choices for different household types in Vietnam, Le (2005) found that for paddy rice-based household type, the paddy rice is more likely chosen for plots farther from the plot owner’s house, closer to rivers/streams, and with less steep slopes; but for off-farm and better-off household type, the choice of paddy rice is more likely affected by dependency ratio and the area of land holding per person. If the target community had many household types with different livelihood assets, farmer adoption of nutrient management practices in response to certain drivers can vary over different household groups (Le, 2005; Le et al., 2012b; Tittonell et al., 2010). Thus, studying on livelihood assets of different household types needs to be taken into account for explaining farmers’ decisions on mineral fertilizer and manure use. So far, analyses of household type-specific determinants of fertilizer use have not yet been found in the current literature, although knowledge about this topic is needed by policy makers and managers to effectively leverage farmers' incentives to invest in measures for reversing land degradation.

The central hypothesis of this research is: different types of households can have different responses to economic and social drivers regarding nutrient input practices. The specific objectives of this study are to:

(1) characterize the diversity of smallholder farming systems in the study area (Yen Chau district, Son La province) by identifying household types; and

(2) identify social and economic determinants of farmers’ decisions on the use of fertilizers (mineral fertilizer use and adoption of manure).

.

## 4.2 Materials and Methods

### 4.2.1 Site description

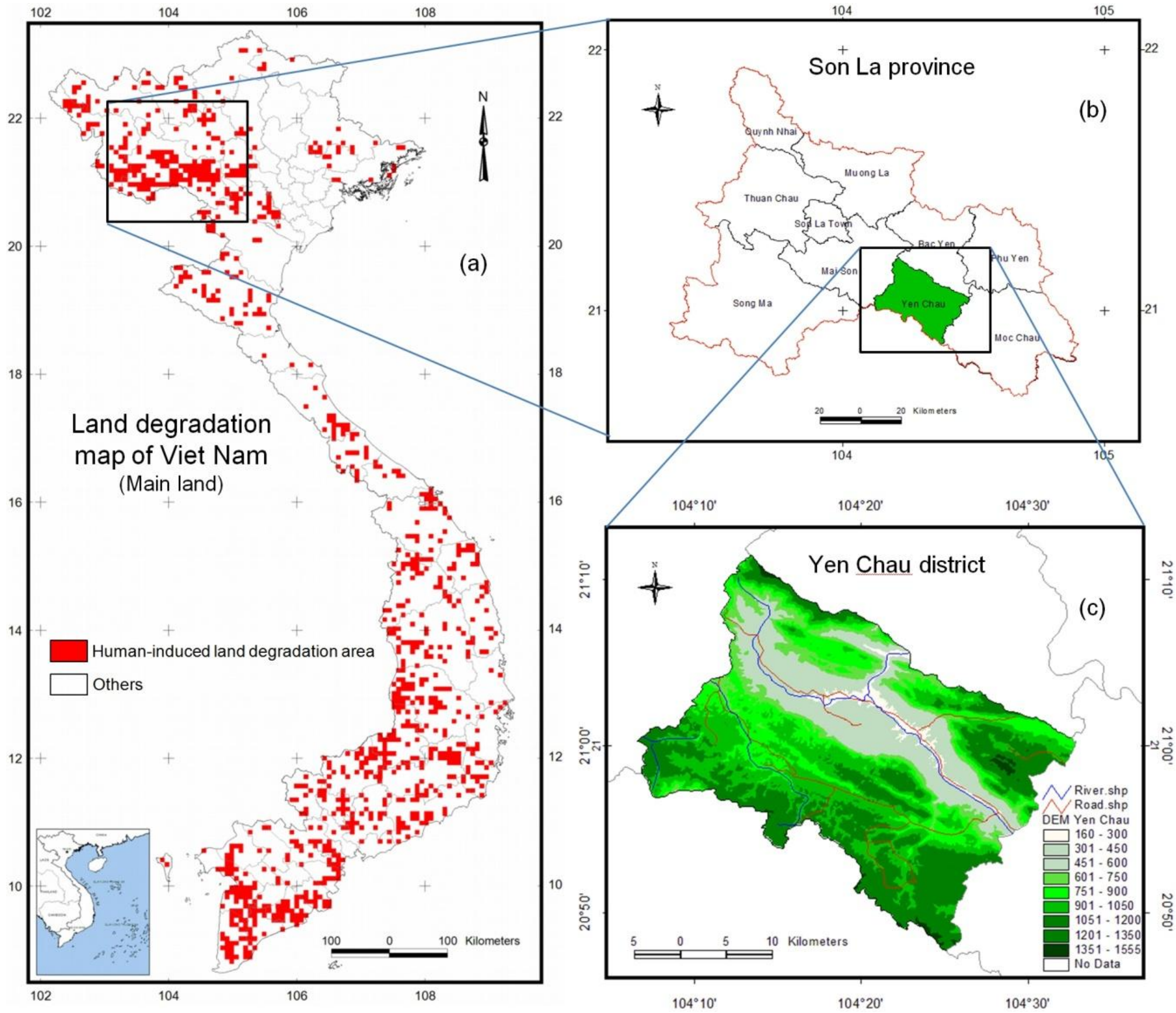


**Figure 4.1** The study area, i.e. Yen Chau district (map (c)) is located in Son La province (map (b)) within the most degraded region of Vietnam (map (a)). Notes: Source of the land degradation hotspot map (a): Vu et al. (2014).

The Yen Chau district in which this study was conducted belongs to the Son La province which is one of the most degraded areas of Vietnam (see Vu et al., 2014) (Figure 4.1). This is a district typical of the uplands in the Northwest Mountains of Vietnam (Quang, 2010). This district has been the focus of many pilot projects by the Vietnamese government to promote agriculture production and forest protection (Keil et al., 2008; Quang, 2010; Quang et al., 2014; Wezel et al., 2002a).

The district is located between $104^0$ 10’ and $104^0$ 40’ E longitude, and between $21^0$ 07’ and $21^0$ 14’ N latitude, covering an area of 859.37 $km^2$. The area comprises 15 communes that belong to two main zones: the area of high mountains (6 communes, at 900–1000 m a.s.l.) and the valley area (9 communes on about 400 m a.s.l.) (Figure 4.1c). Land use systems found in the district are typical for the northwest mountains of Vietnam. On the hill slopes, maize and cassava are cultivated in rainfed fields. Paddy rice is mainly grown on the valley floors nearby the water sources (rivers, streams, and ponds), and in terraced fields on some surrounding hill slopes. Fruit orchards (mainly mango trees) are located nearby residential areas. Recently, maize has become the main cash crop for the farmers in the Yen Chau district as well as in the upland area of Vietnam in general (Keil et al., 2008; Luckmann et al., 2011). Upland crops cover 142 km$^2$ (17% of the total district land). The district has a forest cover of 573 km$^2$ (40% of the total district land). In 2009, the Yen Chau district had 67,994 inhabitants, who belong to five ethnic groups (SDS, 2009). The mountain ethnic groups, comprising more than 70% of the total population, include Black Thai, Hmong, Khmu, and Xinh Mun. The Kinh group, about 30% of the total population, lives mainly in areas close to roads and on flat land. As in many areas of the northwest mountains, agriculture is the major source of livelihood (Fischer and Buchenrieder, 2011; SDS, 2009).

Urea (N= 46%) and water soluble NPK 5-10-3 (nutrient composition: N= 5%, $P_2O_5$= 10%, $K_2O$= 3%) are the two mineral fertilizers used in the district, mainly for rice and maize. The average amounts of mineral fertilizers applied to maize and rice in the households studied in this work are given in Table S4.1. Manure from pig production is the main source of organic fertilizer, and it is usually used for rice because of transportation costs and intensive labor. Manure is mixed with straw or crop/plant residues and stored in brick or concrete containers/pits for 3-4 months before application. Pig manure and cattle and poultry excreta are also used as feed for fish.

### 4.2.2 Sampling procedure and data collection

The data used in this study were derived from an intensive household survey. A stratified sampling design was applied to select 184 households involved in agricultural production in the Yen Chau district. As classified by the District's People Committee, the communes in the district are divided into three main zones based on location and socio-economic conditions. Based on this classification, we used the stratified random sampling method, as shown in the sampling scheme (Figure 4.2). First, at least 30% of communes were selected randomly from each zone in the district. Second, the same procedure was applied to select villages: at least 30% of the villages were selected randomly from each of the selected communes. In the third stage, based on the village's population, about 5 to 15 households in each of 25 selected villages were selected randomly to make up a sample size of 184 for conducting the questionnaire survey.

The household survey was conducted to collect data from household heads from April to September 2011. The topics addressed in the survey were household livelihood characteristics, information about plot holdings and assets, inputs and outputs from the household's activities and the accessibility of the household to agricultural policies/programs. The survey was performed through direct interviews using a structured questionnaire to gather the required information from the sample household. The questionnaires were filled in by trained interviewers under close supervision of the research team. Before conducting the survey, the questionnaire was pretested in selected villages and necessary corrections were made. The household database was used to derive the household's livelihood type and to identify the socio-ecological determinants of nutrient use in the households.

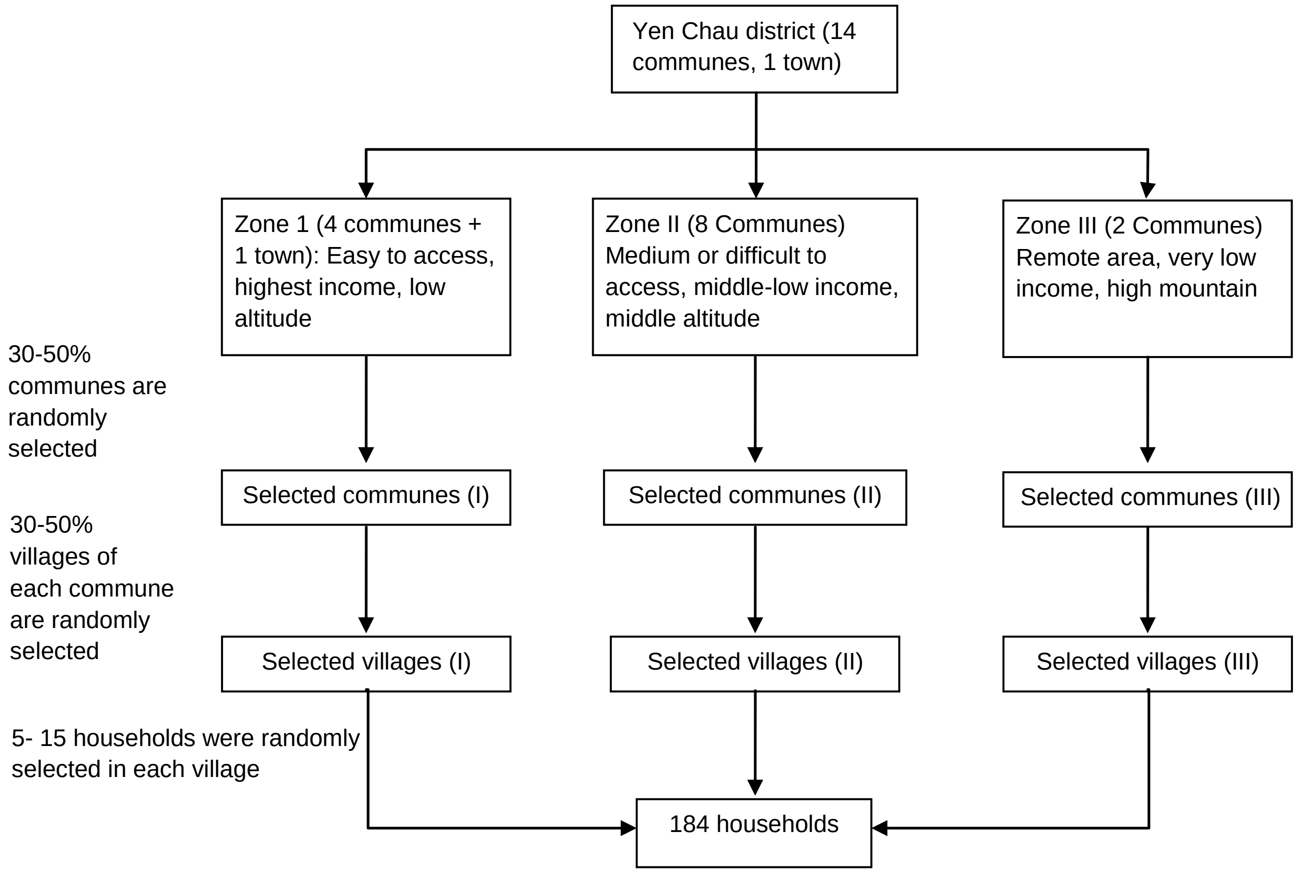


**Figure 4.2** Sampling scheme for the household survey using stratified random sampling method

### 4.2.3 Methods for categorization of household types

The Sustainable Livelihood Framework (SLF) (Bebbington, 1999; Carney, 1998) was used as the conceptual frame to guide the selection of variables for statistical analyses. The core of the framework is five livelihood assets, namely, *physical, human, financial, natural, and social* assets (Ashley and Carney, 1999). This wide range of livelihood assets contains all fields of materials, services, and opportunities available to meet the basic needs of people. We selected 22 potential variables representing the five livelihood assets for our categorization (Table 4.1).

Principal component analysis (PCA) was used to reveal underlying factors differentiating the data clusters. Only principal components with eigenvalues over 1.0 were interpreted in terms of the original variables and used for subsequent analyses. Because the extracted principal components are independent of each other, the use of either these principal components or the original variables strongly correlated with these components, will avoid the problem of multi-collinearity (i.e., significant correlation between explanatory variables) for subsequent analyses. Original variables having significant, strong correlations with the extracted PCs will be used to characterize social, economic, and ecological aspects of the defined household clusters (as the PCs are dimensionless).

The component scores were saved and used as the input variables for K-Means Cluster Analysis (K-CA) to derive the representative groups of households in the district. K-CA is a simple and popular method to find representative classes, or homogeneous groups within a raw dataset (Bradley and Fayyad, 1998; Robinson et al., 2006). Unlike hierarchical clustering methods, K-CA (1) avoids problems of chaining and artificial boundaries, and (2) works on the original input data rather than on a similarity matrix (Kintigh and Ammermann, 1982). To determine the number of clusters, we used the procedure described in Robinson et al. (2006). The optimal cluster number is defined as the minimal cluster number with the highest cluster homogeneity. First, we ran K-CA with the number of clusters set to all values between 2 and 10. For each K-CA (with a concrete *k* value), we calculated the mean distance of cases to their assigned cluster centers. These mean distance values were then plotted against the increasing cluster number (*k* = 2, 3 …, 10). The optimal cluster number was chosen by examining the "elbow" of the curve— the point from which the overall cluster quality, i.e., the reduction of the mean distance from cases to their cluster centers, or the overall cluster homogeneity (Rakhlin and Caponnetto, 2006), is not substantially improved when *k* increases. We characterized the identified clusters using descriptive statistics and applied ANOVA to confirm differences between the clusters. Finally a farm type was assigned to each cluster. The Statistical Package for Social Sciences (SPSS), version 13 for Windows, was used for the above analyses.

.

**Table 4.1** List and descriptive statistics of potential variables considered for principal component analysis (PCA).

| Variable | Definition | Mean | Standard Deviation | Min. | Max. |
|---|---|---|---|---|---|
| Human asset: | | | | | |
| $H_{edu1}$ | Educational level of the household head (school year level) | 6 | 3 | 0 | 12 |
| $H_{edu2}$ | Average education level of household workers (16 < age < 65) | 7 | 3 | 0 | 12 |
| $H_{size}$ | Household size, i.e. number of household members | 5 | 2 | 1 | 9 |
| $H_{labor}$ | Labor availability of the household = number of potential workers (16 < age < 65) | 3 | 1 | 0 | 8 |
| $H_{depend}$ | Dependency ratio = number of children (< 16) and elders (>65) / $H_{labor}$ | 0.5 | 0.5 | 0 | 2.5 |
| Physical asset: | | | | | |
| $H_{trans}$ | Total number of transportation means | 2 | 2 | 0 | 12 |
| $H_{prodtools}$ | Total monetary value of all production tools (1000 VND*) | 3749 | 9695 | 0 | 81950 |
| $H_{a\text{-}power}$ | Animal power index of the household (number of cattle used as power for transportation or land preparation) (head) | 1.9 | 1.5 | 0 | 10 |
| $H_{d\text{-}market}$ | Distance from household to the main market (m) | 2422 | 1744 | 140 | 6363 |
| Natural asset: | | | | | |
| $H_{area}$ | Total farming area of all plots ($m^2$) | 13381 | 8390 | 340 | 46050 |
| $H_{land}$ | Total household farming land per capita ($m^2$/person) | 3029 | 2312 | 170 | 23025 |
| $H_{rice}$ | Share of rice land within the total cultivable area (%) | 10 | 11 | 0 | 100 |
| $H_{maize}$ | Share of maize land within the total cultivable area (%) | 73 | 25 | 0 | 116.4 |
| $H_{pig}$ | Pig weight (kg/year) | 135 | 396 | 0 | 2800 |
| $H_{cattle}$ | Number of cattle (head) | 2 | 2 | 0 | 11 |
| Financial asset: | | | | | |
| $H_{cashinc}$ | Total cash income (cash inflow) during last year (2010) (1000 VND/year) | 493526 | 35947 | 1000 | 250000 |
| $H_{grossinc}$ | Annual gross income of a household (1000 VND) | 57874 | 39649 | 1500 | 261283 |
| $H_{grossincpers}$ | Gross income per capita of a household (1000 VND/person/year) | 12789 | 8738 | 1500 | 65760 |
| $H_{cropincshare}$ | Share of gross crop income (%) | 58 | 25 | 0 | 100 |
| $H_{livesincshare}$ | Share of gross livestock income (%) | 13 | 17 | 0 | 97 |
| $H_{otherincshare}$ | Share of other (non-farm) income (%) | 29 | 25 | 0 | 100 |
| Social asset | | | | | |
| $H_{org}$ | Organizational membership of the household (0= No membership, 1 = at least one household member has a position in association/organization) | 1 | 0 | 0 | 1 |

Source: Field survey 2011. Summary statistics are based on 184 cases without missing values for any of the variables

*Vietnam Dong (VND): 1 USD = 20,540 VND at the time of survey in Jun 2011

### 4.2.4 Methods for identifying socio-ecological determinants of smallholders' decisions on fertilizer use

After having identified the household types for the district, we used multiple linear regression and binary logistic regression in SPSS to examine independently for each household type identified in 4.2.3 the relationship between the hypothesized variables (see Table 4.2) and the farmers' decisions on mineral fertilizer use (*MFU*), and adoption of manure use (*MU*).

#### 4.2.4.1 Dependent variables and regression methods

*Mineral fertilizer use (MFU)*

Mineral fertilizer use (*MFU*) was calculated for each household as the sum of N, P2O5 and K2O added as urea and NPK 5-10-3 expressed in kg per hectare per year.

We used multiple linear regression (MLR) to determine factors that explain mineral fertilizer use (*MFU*) for each household type identified in step 4.2.3. The relationship of *MFU* to the hypothesized explanatory variables was described as follows:

$$MFU = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \mu \quad (1)$$

where $X_i$ and $\beta_i$ ($i$ = 1, 2, 3, …, $n$) are explanatory variables and their weights, respectively. These variables are obtained from a field survey, as shown in Table 4.2.

The performance of the MLR model was evaluated by (1) examining the overall significance of the regression model using $F$-statistics, (2) measuring the model's goodness-of-fit using $R^2$, and (3) testing the statistical significance of partial causal effects by examining $p$-values. For MLR model based on cross-sectional data such as the present study, an $R^2$ value of around 0.5 should indicate good model performance (Greene, 2012).

*The adoption of manure use (MU)*

In the study area, farmers use animal manure in paddy rice. The variable for manure use adoption (*MU*) has a dummy scale: 1 if the households apply manure to their paddy field, and 0 otherwise.

Binary logistic regression (bi-logit) was applied to identify factors determining manure use adoption for each household type identified in step 4.2.3. The logistic regression equation is useful for dichotomous dependent variables. The effect of the hypothesized socio-ecological variables on the adoption of manure by a household can be modeled as equation (2):

$$P_{(MU)} = 1 / (1 + e^{-(\beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \ldots + \beta nXn + \mu)}) \quad (2)$$

where $P_{(MU)}$ is the probability of manure use adoption. $X_i$ and $\beta_i$ ($i$ = 1, 2, 3, …, $n$) are explanatory variables and their weight coefficients, respectively. $\mu$ is a random error term.

Our performance evaluation of binary logistic regressions included (1) a chi-squared test for the overall statistical significance of the regression model, (2) the probability of correct prediction, and (3) Receiver Operating Characteristic (ROC) statistics (see more details in Vu et al., 2014).

#### 4.2.4.2 Hypothesized explanatory variables

We identified variables explaining *MFU* and *MU* based on causal hypotheses that were justified in the first instance by literature reviews. The summary of eleven hypothesized explanatory variables is given in Table 4.2. The justification for their hypothetical effects on *MFU* and/or *MU* is described in the following paragraphs.

**Table 4.2** Description and predicted signs of effect by different variables used in multiple linear regression for mineral fertilizer use and binary logistic regression for adoption of manure

| Variable | Description | Unit | Hypothesized effect* | |
|---|---|---|---|---|
| | | | MFU | MU |
| Dependent variable | | | | |
| *MFU* | Mineral fertilizer use | kg/ha/year | | |
| *MU* | Adoption of manure (1: adopted; 0: not adopted) | Dummy | | |
| Explanatory variable | | | | |
| $H_{edu1}$ | Educational level of the household head | year | + | + |
| $H_{size}$ | Household size | Person/ household | +/- | +/- |
| $H_{depend}$ | Dependency ratio | | - | - |
| $H_{prodtools}$ | Total monetary value of all production tools | 1000 VND | + | + |
| $H_{d\text{-}market}$ | Distance from household to the market | m | + | + |
| $H_{land}$ | Household's farming area per capita | $m^2$/person | +/- | +/- |
| $H_{rice}$ | Share of rice area within household's farming area | % | + | + |
| $H_{maize}$ | Share of maize area within household's farming area | % | + | + |
| $H_{pig}$ | Weight of household's pigs | kg/year | - | + |
| $H_{grossincpers}$ | Gross income per capita of a household | 1000 VND/ person/ year | + | + |
| $H_{org}$ | Organizational membership of the household (1 = at least one household member has a position in association/organization, 0= otherwise) | Dummy | + | + |

*(+) indicates a positive expected influence of that variable on the nutrient use; (-) indicates a negative effect; (+/-) indicates potentially ambiguous outcomes.

*Variables for human asset*

The educational level of the household leader ($H_{edu1}$) represents the knowledge of a farmer, for instance on environmental problems. Farmers with better education can apply recommendations better, or have better knowledge about fertilizer use in crop production (Karanja et al., 1998; Zhou et al., 2010). Therefore, educational level is expected to be positively associated with the mineral fertilizer use and adoption of manure.

Household size ($H_{size}$) constrains input for agricultural production and is likely to positively affect a household’s decision to adopt and use fertilizer (Kherallah et al., 2001; Nkonya et al., 1997). Households with more members might tend to apply more fertilizers to increase crop production in order to meet the household demands. Moreover, large households also represent a large labor supply for farming operations. However, due to the competing needs of a large household size for other household necessities (Zhou et al., 2010), investment in fertilizer may be restricted. Therefore, the influence of household size on nutrient inputs is expected to be ambiguous.

The dependency ratio ($H_{depend}$) reflects the number of persons each working household member feeds; thus, it relates to the urgency of food demands of the household (Fatoux et al., 2002). Households with more dependents are likely to produce more subsistence crops to meet food security needs (Omamo et al., 2002). Therefore, farmers with more dependent members are expected to use more mineral fertilizer and manure in crop production.

*Variables for social asset*

Organizational membership of the household ($H_{org}$) reflects the participation of a household in a local social organization or union (e.g., farmers' association, women's association, or veterans' organization). This social activity and membership can benefit the household by providing help, knowledge, and experience through interactions with other farmers that promote the farmer's learning of improved nutrient management practices. Thus, it is expected that organizational membership of the household would be positively related to mineral fertilizer use and adoption of manure.

*Variables for natural asset*

Total household farming land per capita ($H_{land}$) is often an indicator of land scarcity that calls for the intensification of holding lands, and it is expected to be an important driver of nutrient use. In a common sense, households having large rain-fed cropping land may have not enough man-power and/or financial resource to intensify all their crop fields. However, some households with large farm size can be the better-off families who have enough financial capacity, and probably expect to invest to increase areas of cash and food crops, or to increase crop rotation and fertilizer input to their fields (Akpan and Aya, 2009; Amanze et al., 2010; Likita, 2005; Waithaka et al., 2007). At the same time, households with little farming land also have to increase their crop productivity to meet their demands; thus, production has to be intensified and more fertilizer added. Therefore, the expected effect of this variable on mineral fertilizer use and manure adoption was ambiguous.

Rice and maize are the major crops in the area. We hypothesized that households with more area devoted to rice ($H_{rice}$) or maize ($H_{maize}$) might use more fertilizer, and adopt manure more often, compared to others.

Pig production provides animal manure that can be applied as fertilizer on crops. A study conducted in northern Vietnam (Tran et al., 2012) showed that the nutrient concentration in fresh pig manure was around 30.2 g/kg dry matter of total N; 32.4 g/kg dry matter of total P, 7.5 g/kg dry matter of total K. Therefore, we hypothesized that a household with more pigs, measured by weight per year ($H_{pig}$), might adopt more manure and apply less mineral fertilizer than others.

*Variables for physical asset*

Total monetary value of all production tools ($H_{prodtools}$) represents the cultivation and agricultural production capacity of a household. Households with better production tools including animal power may have advantages in transporting products, preparing soils, applying fertilizers, etc.; thus we hypothesized that this variable would correlate positively with mineral fertilizer use and the adoption of manure.

Distance to market ($H_{d\text{-}market}$) reflects the accessibility to the market for buying agricultural inputs (e.g., fertilizer, pesticides, and seeds) and selling the harvest of a household. This is an important determinant of land use patterns (Pandey and van Minh, 1998). The household groups located near the market may easily sell agricultural products and buy other food, goods, and tools for their living and crop production. It means that a short distance to market will reduce the costs of inputs (Waithaka et al., 2007), which may increase investment in mineral fertilizers for crop production. With the household groups living far from the market, the high cost of transport restricts trading; farmers may prefer to use more organic sources. Therefore, distance to the market was expected to be negatively correlated to mineral fertilizer use and positively correlated to adoption of manure.

*Variables for financial asset*

Gross income per capita ($H_{grossincpers}$) represents the wealth of a household and is an important factor affecting the investment in upland farmers' agricultural production. We hypothesized that farmers with a higher gross income per capita would have the ability to finance the purchase of agricultural inputs, which might lead to more fertilizer use.

## 4.3 Results

### 4.3.1 Household typology

#### 4.3.1.1 Factors explaining the differences in household types

The PCA run extracted nine principal components with total eigenvalues greater than 1.0, explaining 82% of the total variance of the original independent variables. The rotated component matrix then helped to determine what the components represent (Table 4.3).

The principal component 1 (PC1) was strongly related to income variables (i.e., gross income $H_{grossinc}$, gross income per capita $H_{grossincpers}$, and cash income $H_{cashinc}$, with loading factors more than 0.8). Thus, we named this component "income factor". The income factor accounted for 20.7% of the total variance of the original dataset. Pair correlations among these three variables showed they were highly multicollinear. Because gross income per capita ($H_{grossincpers}$) had a very high loading and a more economic meaning than the two others, this variable was chosen as the representative for the income factor.

Principal component 2 was most weighted by livestock variables, i.e., pig weight (loading $b$ = 0.81) and share of gross livestock income (loading $b$ = 0.89). Thus, we labeled the component "livestock factor". This factor accounted for 13.3% of total variance of the original dataset. These two variables were strongly correlated ($r$ = 0.74), but $H_{pig}$ was selected as the representative for the PC because it is more meaningful.

Principal component 3 was most highly correlated with labor availability, $H_{labor}$ ($b$ = 0.86), and household size, $H_{size}$ ($b$ = 0.92); so it was called the "labor factor". The pairwise correlation of the two variables showed that they were strongly correlated ($r$ = 0.75). Because of the high loading value, household size ($H_{size}$) was selected to represent the labor factor.

Principal component 4 was highly correlated with the share of gross crop income, $H_{cropincshare}$ ($b$ = 0.88); thus, it was called the "crop factor".

Principal component 5 was explained mainly by the animal power index, $H_{a\text{-}power}$ ($b$ = 0.93), and number of cattle, $H_{cattle}$ ($b$ = 0.92). Accordingly, we called this component the "cattle factor". Number of cattle ($H_{cattle}$) was selected for this PC because it seems more meaningful and covers the properties of both variables.

Principal component 6 was related mainly to total household farming land per capita, $H_{land}$ ($b$ = 0.73), and total household farming area of all plots, $H_{area}$ ($b$ = 0.68); therefore, we called this component "land factor". Because of its higher loading and to better reflect land area allocation, total household farming land per capita ($H_{land}$) was selected for this PC.

**Table 4.3** The loading value of potential variables with respect to the nine principal components

| Variable | Component | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| | Income | Livestock | Labor | Crop | Cattle | Land | Production tool | Education | Dependents |
| $\boldsymbol{H_{edu1}}$ | -0.04 | 0.07 | -0.14 | 0.03 | -0.02 | 0.04 | 0.00 | **0.91** | 0.04 |
| $H_{edu2}$ | 0.08 | 0.00 | 0.26 | -0.09 | 0.03 | -0.08 | 0.07 | **0.84** | -0.10 |
| $\boldsymbol{H_{size}}$ | 0.06 | 0.00 | **0.92** | 0.10 | 0.22 | 0.01 | 0.07 | 0.02 | 0.21 |
| $H_{labor}$ | 0.11 | -0.04 | **0.86** | 0.05 | 0.14 | -0.01 | 0.12 | 0.11 | -0.40 |
| $\boldsymbol{H_{depend}}$ | -0.02 | -0.05 | -0.04 | 0.01 | 0.04 | 0.02 | -0.12 | -0.05 | **0.94** |
| $H_{trans}$ | 0.06 | 0.02 | 0.08 | 0.04 | 0.02 | 0.01 | **0.89** | 0.05 | -0.15 |
| $\boldsymbol{H_{prodtools}}$ | 0.18 | -0.01 | 0.06 | -0.06 | 0.00 | 0.05 | **0.87** | 0.02 | 0.00 |
| $H_{apower}$ | -0.01 | -0.05 | 0.14 | 0.01 | **0.93** | 0.04 | 0.04 | 0.01 | 0.04 |
| $H_{d\text{-}market}$ | 0.56 | -0.42 | 0.03 | 0.25 | -0.13 | -0.15 | 0.00 | 0.04 | 0.12 |
| $H_{area}$ | 0.44 | -0.20 | 0.29 | 0.24 | 0.22 | **0.68** | -0.01 | -0.01 | -0.08 |
| $\boldsymbol{H_{land}}$ | 0.30 | -0.20 | -0.28 | 0.19 | 0.12 | **0.73** | -0.05 | -0.08 | -0.25 |
| $H_{rice}$ | -0.15 | 0.60 | 0.03 | -0.27 | -0.07 | -0.22 | 0.09 | -0.03 | -0.09 |
| $H_{maize}$ | 0.13 | -0.28 | -0.07 | 0.50 | 0.01 | -0.61 | 0.04 | 0.10 | 0.05 |
| $\boldsymbol{H_{pig}}$ | 0.37 | **0.81** | -0.04 | 0.05 | -0.02 | 0.01 | 0.01 | 0.09 | -0.06 |
| $\boldsymbol{H_{cattle}}$ | 0.09 | 0.01 | 0.13 | 0.04 | **0.92** | 0.02 | -0.01 | 0.00 | -0.03 |
| $H_{grossinc}$ | **0.81** | 0.14 | 0.33 | -0.01 | 0.17 | 0.18 | 0.27 | 0.05 | -0.08 |
| $\boldsymbol{H_{grossincpers}}$ | **0.81** | 0.29 | -0.15 | -0.05 | 0.09 | 0.19 | 0.21 | 0.05 | -0.22 |
| $\boldsymbol{H_{cropincshare}}$ | -0.05 | -0.28 | 0.08 | **0.88** | 0.05 | 0.10 | -0.02 | -0.08 | 0.02 |
| $H_{livesincshare}$ | 0.08 | **0.89** | 0.00 | 0.02 | -0.02 | 0.03 | 0.00 | 0.09 | -0.01 |
| $H_{otherincshare}$ | 0.00 | -0.35 | -0.08 | **-0.91** | -0.04 | -0.12 | 0.01 | 0.02 | -0.01 |
| $H_{cashinc}$ | **0.82** | 0.11 | 0.32 | -0.03 | 0.14 | 0.16 | 0.29 | 0.04 | -0.07 |
| $H_{org}$ | -0.06 | 0.01 | 0.04 | 0.10 | -0.04 | 0.56 | 0.19 | 0.05 | 0.28 |

Note: Bold variables are those with both high loading factor (highly correlative with the PC) and underlined variables those selected for representing the extracted PC (see text for details).

Principal component 7 was strongly associated with transportation means, $H_{trans}$ (b = 0.89), and total monetary value of all production tools, $H_{prodtools}$ (b = 0.87); so it is called the "production tool factor". With respect to agricultural production, tools are the more meaningful of the two, so we selected $H_{prodtools}$ as the representative for this PC.

Principal component 8 was explained mainly by the educational level of the household head and workers, thus we named it the "education factor". Educational level of the household head ($H_{edu1}$) with a higher loading value was represented by PC8.

Principal component 9 was most strongly related to the dependency ratio, $H_{depend}$ (b = 0.94). This component was named the "dependency ratio factor".

#### 4.3.1.2 Socio-ecological types of household

The K-CA run—using standardized scores of the nine principle components—identified six socio-ecological household types. The characterization using key variables for each household type is shown in Figure 4.3.

.

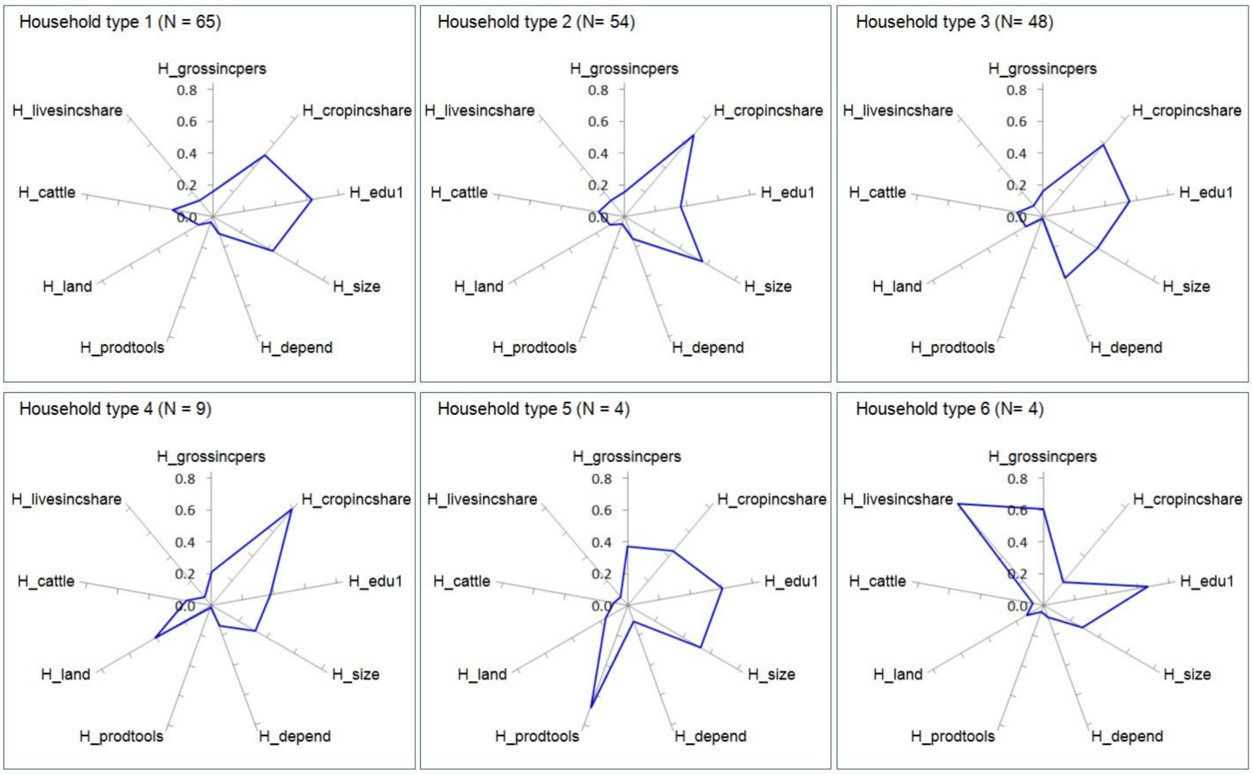


**Figure 4.3** Spider diagrams showing 9 key social and economic variables representing 9 principal components for the six household types in Yen Chau district. Data of all variables were normalized using the equation: $x_{norm} = (x - x_{min})/(x_{max} - x_{min})$. The descriptive statistics of all variables are shown in Table S4.2 (Supplementary Information).

*Household type 1* (*n* = 65): *The poor households with higher education level and a preference for cattle.* The group constitutes about 35% of the total surveyed households. The ethnic groups include Thai, Kinh and Xinh Mun. The spider diagrams of normalized data of the 9 principle factors found in the last step showed that this group consists of households with low income, higher education and a high number of cattle (Figure 4.3). The household heads of this type have a higher educational level than almost all other types. On average, each household in this group has three heads of cattle, and the gross income per person ranges from 10 to 13 million VND per year (i.e. is below 2 USD per day).

*Household type 2* (*n* = 54): *The poor household with low education and a preference for pig production.* The group constitutes about 29% of the households interviewed. As for type 1, there are three ethnic groups (Thai, Kinh, and Xinh Mun) in this group. The head of households in this group is less educated than in other groups. They are also poor and have less farming land per person. Each person of this household type holds land of 460–5,100 $m^2$ and has an average gross income of about 11.6 million VND per year. The households raise more pigs, and the income from livestock is a bit higher than that of other household types, except type 6 (Table S4.2). Thai people dominate this group.

*Household type 3* (*n* = 48): *The poor households with few man power and many dependents*. The main characteristics of this household group include a lack of labor and a high dependency ratio. On average, each household has two workers, and each worker has to feed at least one dependent person. The households are poor; the average of gross income per person is about 12 million VND per year. About 26% of sampled households belong to this household type. Thai and Xinh Mun ethnic people dominate this group.

*Household type 4* (*n* = 9): *The poor farms with less educated farmers and crop production preference*. The group comprises about 5% of the sample and is peopled mostly by Thais. This household type is the group that typically relies mostly on income generated by crop production. The percentage of crop income ranges from 60 to 100% of the total income. They own more land for agricultural production (i.e., the area per person is 6,000 $m^2$ to 23,000 $m^2$). This household type is poor (i.e., the average of gross income per person is 15.2 million VND per year).

*Household type 5* (*n* = 4): *The better-off households relying on non-farm activities*. The spider diagrams (Figure 4.2) show that this type represents a category of households that relies on non-farm activities. They own some machines (milling machine, small tractors, vans, etc.) for hire, and they can earn money from hiring activities. The gross income per capita of the household type is medium (about 25 million VND per year, on average). This household type comprises only about 2% of the sampling population. The group consists of Kinh and Thai people.

*Household type 6* (*n* = 4): *The richest farms that rely on pig production*. Comprising only a low proportion of the sampling population (about 2%), this household type represents the pig farmers in the study area. The weight of pigs that the household produces per year ranges from 1200–2800 kg, making this livestock the main income source for this household type. These households are richer than all other groups, with an average gross income per person of 40 million VND per year. Like household type 5, this group is split between Thai (77%) and Kinh people (33%).

### 4.3.2 Determinants of smallholders' decisions on mineral fertilizer use

Only three main household types were large enough for multiple regression analysis (types 1, 2, and 3 with $n$ = 65, 54 and 48). We also conducted regression analyses for the household population that combined the three household types mentioned above ($n$ = 167) to compare if there was any difference between the effects of hypothesized explanatory variables on fertilizer use in the combined population and those in household type-specific sub-populations.

The result of the MLR analysis, with mineral fertilizer use as the dependent variable is shown in Table 4.4. An $F$-test indicated that the MLR models for different household types were significantly different at the 0.1% level. The models had good prediction power ($R^2$ > 0.5 for all three types).

**Table 4.4** Results of multiple linear regression analyses for identifying determinants of the mineral fertilizer use for different household types

| *Variable* | *Estimated β coefficient* | | | |
|---|---|---|---|---|
| | *Combination of 3 main household types (N =167)* | *Household type 1 (N = 65)* | *Household type 2 (N =54)* | *Household type 3 (N =48)* |
| $H_{edu1}$ | -1.696 | 0.766 | 0.673 | 7.179 |
| $H_{size}$ | **55.078*** ** | **45.926*** ** | **47.400*** ** | 29.210 |
| $H_{depend}$ | **-40.333*** | 17.447 | -2.554 | -9.730 |
| $H_{prodtools}$ | 0.001 | -0.002 | -0.001 | **0.025** ** |
| $H_{d\text{-}market}$ | -0.004 | 0.018 | -0.008 | 0.002 |
| $H_{land}$ | **0.026** ** | **0.031*** | 0.039 | **0.030*** |
| $H_{rice}$ | -0.576 | -0.347 | -1.366 | 3.084 |
| $H_{maize}$ | **0.967*** | **1.277*** | -1.056 | -0.612 |
| $H_{pig}$ | 0.009 | -0.039 | -0.007 | 0.068 |
| $H_{grossincpers}$ | **0.009*** ** | **0.009*** ** | **0.014*** ** | 0.000 |
| $H_{org}$ | -34.409 | 1.375 | -17.796 | **-191.663*** ** |
| Intercept | -170.240 | -263.256 | -47.047 | 131.326 |
| *F-test* | $F$ = 11.197, $df$ = 11, $p$ < 0.001[a] | $F$ = 4.981, $df$ = 11, $p$ < 0.001[a] | $F$ = 4.142, $df$ = 11, $p$ < 0.001[a] | $F$ = 3.120, $df$ = 11, $p$ < 0.005[a] |
| $R^2$ | 0.448 | 0.508 | 0.526 | 0.502 |
| *adjusted-$R^2$* | 0.408 | 0.406 | 0.399 | 0.341 |

Notes: *, **, and *** indicate a statistical significance at 90% ($p$ < 0.1), 95% ($p$ < 0.05), and 99% ($p$ < 0.01), respectively.

[a] $p$ < 0.001 indicates that there is a statistically significant relationship (99% confidence level) between the dependent variable and the hypothesized explanatory variables.

As depicted in Table 4.4, mineral fertilizer use increased significantly ($p$ < 0.01) with increased household size and higher gross income per capita ($H_{grossincpers}$) for household types 1 and 2. Besides, for household type 1, farming land per capita ($H_{land}$) and share of area for maize cultivation ($H_{maize}$) showed positive and significant correlation ($p$ < 0.10) with mineral fertilizer use. For household type 3, the value of all production tools ($H_{prodtools}$) and farming land per capita

($H_{land}$) were positively correlated (significant at the 5% and 10% level) with mineral fertilizer use. Organizational membership ($H_{org}$) produced a negative effect, significant at the 1% level, meaning that the amount of fertilizer used decreases when at least one household member has a position in a local association or organization. Educational level of the head of household ($H_{edu1}$), dependency ratio ($H_{depend}$), distance from the household to the main market ($H_{d\text{-}market}$), share of area for rice cultivation ($H_{rice}$) and pig weight ($H_{pig}$) did not significantly influence the amount of fertilizer used for any household type.

Almost explanatory variables found in the combined population regression analysis which showed significantly correlation with mineral fertilizer use were those found in household type-specific regression analyses (Table 4.4). However, we also found some differences between these analyses. With a total of 167 households, the dependency ratio ($H_{depend}$) showed a negative correlation (significant at the 5% level) with mineral fertilizer use, whilst this factor was insignificant in household type-specific regressions. This may be not a surprise, because the small size of household type-specific sub-populations may limit the statistical power of the correlation between the dependency ratio and mineral fertilizer use. On the contrary, the factors of production tools ($H_{prodtools}$) and organizational membership ($H_{org}$) were insignificant for explaining mineral fertilizer use with the combined population, but were significant in determining the fertilizer use in household type 3.

### 4.3.3 Determinants of smallholders' decision on the adoption of manure

The results of binary logistic regression for identifying determinants of organic fertilizer adoption for different household types are presented in Table 4.5. The Hosmer and Lemeshow test for the bi-logit models resulted in a $p$-value of around 0.6 (> 0.05), which showed no statistically significant difference between the predicted data for manure adoption and the observed data, meaning that there is a good fit of the model to the data. The percentage of corrected predictions of the models were very high for every household type (more than 80%), and the calculated area under the ROC curve ranged from 0.88 to 0.93, indicating that the performance of the models varies from excellent to outstanding for identifying the determinants of adoption of manure.

The determinants of adoption of manure varied for the different household types. The results of bi-logit test for household type 1 showed that the dependency ratio ($H_{depend}$) and the distance to the market ($H_{d\text{-}market}$) were significant at the 10% level, but $H_{depend}$ had a positive and $H_{d\text{-}market}$ had a negative effect on the adoption of manure. These results indicate that the farms with more dependents were more likely to use manure than the farms with a low dependency ratio, and those farmers were less likely to adopt manure with an increasing distance to the main market. The adoption of manure on a farm by household type 2 was related to the household size ($H_{size}$) and its share in an area of rice cultivation ($H_{rice}$). Both factors showed a positive effect, but the significance level of $H_{rice}$ is stronger (at $p < 0.05$) than that of $H_{size}$ (at $p < 0.10$). Households of this type would be more likely to adopt manure for agricultural production when they have more land for rice cultivation and more people in the family. For household type 3, the adoption of manure on a farm increased significantly with increasing share in an area of rice ($H_{rize}$) and maize cultivation ($H_{maize}$), at significance levels of 1% and 10%, respectively. Moreover, similarly to household type 1, type 3 households were less likely to adopt manure with increasing distance to the main market ($H_{d\text{-}market}$).

Comparing the results of the three household groups, taken separately, to the combination of the three types, we found that educational level of the head of household ($H_{edu1}$), dependency ratio ($H_{depend}$), share of area for maize cultivation ($H_{maize}$), and gross income per capita ($H_{grossincpers}$) showed different correlations with manure adoption . $H_{edu1}$ and $H_{depend}$ are positively correlated with manure adoption for household type 1, but insignificantly so for the other groups (Table 4.5). $H_{grossincpers}$ is an important factor for the combination of three types, but when considering each household type separately, it is insignificant.

**Table 4.5** Results of binary logistic regression for identifying determinants of the organic fertilizer adoption for different household types

| *Variable* | *Estimated β coefficient* | | | |
|---|---|---|---|---|
| | *Combination of 3 main household types (N =167)* | *Household type 1 (N = 65)* | *Household type 2 (N =54)* | *Household type 3 (N =48)* |
| $H_{edu1}$ | 0.081 | **0.500*** | 0.003 | -0.281 |
| $H_{size}$ | **0.401*** ** | 0.367 | **0.646*** | 0.825 |
| $H_{depend}$ | -0.126 | **6.742*** | -1.329 | 0.066 |
| $H_{prodtools}$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $H_{d\text{-}market}$ | **0.000*** ** | **-0.001*** | -0.001 | **-0.001** ** |
| $H_{land}$ | 0.000 | 0.001 | 0.000 | -0.001 |
| $H_{rice}$ | **0.096*** ** | -0.078 | **0.186** ** | **0.360*** ** |
| $H_{maize}$ | 0.008 | 0.016 | -0.019 | **0.051*** |
| $H_{pig}$ | 0.001 | 0.256 | -0.001 | 0.006 |
| $H_{grossincpers}$ | **0.000*** | 0.000 | 0.000 | 0.000 |
| $H_{org}$ | -0.917 | -1.242 | -0.885 | -1.182 |
| Intercept | -1.457 | -4.787 | -1.734 | -4.064 |
| *Hosmer and Lemeshow test* | Chi-square = 4.19, *df* = 8, *p* = 0.839[a] | Chi-square = 5.23, *df* = 7, *p* = 0.632[a] | Chi-square = 6.22 *df* = 8, *p* = 0.623[a] | Chi-square = 14.59 *df* = 8, *p* = 0.656[a] |
| *%corrected prediction* | 78.4 | 90.8 | 81.5 | 87.5 |
| *Nagekerke $R^2$* | 0.378 | 0.605 | 0.518 | 0.656 |
| *Area under ROC* | 0.834[b] | 0.933[b] | 0.878[b] | 0.929[b] |

Notes: *, **, and *** indicate a statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$), and 99% ($p < 0.01$), respectively.

[a] $p > 0.05$ indicates that there is no statistically significant difference (95% confidence level) between the observed and predicted data of the dependent variable.

[b] benchmarks for the area under ROC: 0.5–0.7: better than chance; 0.7–0.8: acceptable performance; 0.8–0.9: excellent performance; 0.9–1.0: outstanding performance (Hosmer and Lemeshow, 2000).

## 4.4 Discussion

### 4.4.1 Categorizing household types

Results from the household grouping showed that the poor, crop-based production households comprised most of the population (35 % of the total surveyed households), while the wealthier farmers who have off-farm activities constitute only a very small part of the population (2 % of the total surveyed households). The results are consistent with the poverty map of Vietnam (Minot and Baulch, 2005) as Yen Chau is located in the poorest part of the country (Fischer and Buchenrieder, 2011). The result also reflect the livelihood patterns given by the district statistics in 2008, i.e., 85 % of the district's population are agriculture-based households and largely poor (SDS, 2009).

We observed mixed ethnicities in most of the household types. The Thai, Kinh, and Xinh Mun ethnic groups appeared in five household types, except household type 4, which was purely Thai. This indicates that ethnicity is no longer an important factor in distinguishing household types. The finding is consistent with the analysis of Castella et al. (2002) on the uplands of northern Vietnam, which indicated that the role of ethnicity in household differentiation has been reduced over the last fifty years.

### 4.4.2 Mineral fertilizer use

The significant positive correlation between household size and amount of fertilizer used indicates that large families tend to use more fertilizer to improve agricultural production in order to meet the family needs. This result is also consistent with past studies conducted in Africa (Minot et al., 2000; Olayide et al., 2009), where mineral fertilizer use was found to increase with household size. However, in our study, it is true for household types 1 and 2, but not for household type 3, due to the lack of labor forces and the presence of more dependents in this household type.

Higher gross income per capita is correlated with an increased use of mineral fertilizer in household types 1 and 2. This correlation is as expected. It means that households with higher incomes are able to satisfy their basic demands and are willing to pay money to buy fertilizer to increase crop yields (mainly maize and rice). The finding corroborates the results of Waithaka et al. (2007) for Kenya and of Akpan and Aya (2009) for Nigeria.

The results also show that for household type 1, farmers with more farm land per capita are likely to use more fertilizer. Again this finding is consistent with results from previous studies in Africa (Akpan and Aya, 2009; Amanze et al., 2010; Aregay and Minjuan, 2012; Minot et al., 2000; Waithaka et al., 2007). This could be explained by the fact that in the Yen Chau district, farmers usually organize themselves better and invest in inputs when they have an area large enough to be worthy of investment.

The area of maize is a positive determinant of mineral fertilizer use among type 1 households. The results indicate that for this household type farmers who have more area under maize cultivation apply more mineral fertilizer than farmers with less maize area. Beside the new maize varieties that grow well in the study region, mineral fertilizers are the major inputs needed to reach the desired yield (Ha et al., 2004). Unexpectedly, the participation of at least one member of a household in a local organization decreases mineral fertilizer use, but this effect is significant only for household type 3. The farmers in this household type may have learnt to use their fertilizers more efficiently in these organizations and so need to apply less than the other farmers.

### 4.4.3 Adoption of manure

During the field survey, we recognized that the major source of organic fertilizer comes from animal production on farm, of which pig production is the most important source. There is no organic fertilizer trading in the study area. The significant positive correlation between household size and the adoption of manure matched our expectation. Since manure collection, preparation and application are labor intensive (Makokha et al., 2001), households with large families and more labor force are more likely to adopt manure.

The results for household type 1 indicate that the farmers with a better educational level and more dependents are more likely to adopt manure than the farmers with a low dependency ratio; while farmers are less likely to adopt manure with increasing distance to the main market. Better educational level of the household leader of this household type may help farmers increase their perception that manure application is useful. Given the topography of the mountain landscape, distance increases not only the time to access the market, but also the transaction cost of using fertilizers (e.g. time and labor needs for carrying fertilizers to remote cropping fields) (Minot et al., 2000). Therefore, households located far from the market ought to tend to use manure as much as they can to substitute for mineral fertilizers. However, this is not consistent with our finding in Yen Chau district, since we found that farmers are less likely to adopt manure when their houses are further away from the main market. For farms located further from markets, transaction costs for pig production are also higher (e.g., transaction costs for buying feed and selling meat), likely resulting in less intensive pig production and subsequently lower manure production. The study on smallholder pig production systems in Son La province by Lemke and Valle Zárate (2008) indicated that farmers living near markets prefer to raise pig than those located away from markets who mainly focus on crop production.

For household types 2 and 3, the results show that farmers with more area under rice cultivation tended to adopt manure more than others. The results imply that manure is more important to the production of food crops (rice) than cash crops (maize). This finding is consistent with the study in Africa of Waithaka et al. (2007), which found that the increase of cash crop area was likely to reduce manure use. In the upland area, most farmers realize that manure is useful for maize cultivation and for improving soil fertility, but manure is little used on maize, because its application is labor-intensive (Ha et al., 2004). This is confirmed by the result shown in Table 4.5, which indicates that most households do not adopt manure for maize cultivation.

### 4.4.4 Limitations and recommendations

There are still some limitations in the approach and methods of the present study. First, in analyzing the nutrient uses for the household types, we considered the total amount of N, P and K fertilizers used as the dependent variable. Examining the input and the output of each element separately would be another option. For instance, Miao et al. (2011) and Zhang et al. (2006) indicated that there was excessive N and P inputs but but a lack of K inputs in cropping systems in China. The same might be true in our study (Table S4.1). These variables could be included in further studies on the same topic.

Soil quality is an important feature not considered in the present work. Marenya and Barrett (2009) showed that different soil quality (assessed through soil carbon content) significantly affected the behavior of western Kenyan farmers in fertilizer application. Fertilizer use rates are strongly and positively correlated with soil carbon content (SCC) in the high SCC plots (SCC above 2.7%), where increased fertilizer use becomes remunerative (Marenya and Barrett, 2009). However, soil fertility is difficult to incorporate at the household level in this study. As each household usually has many plots (5–20 plots) in different locations, it is very difficult to express that soil variation at household level. More time- and cost-efficient methodologies for soil analysis such as near-infrared (NIR) and mid-infrared (MIR) spectroscopic techniques (Cozzolino and Moron, 2003; Shepherd and Walsh, 2002) may solve the problem and should be used in future studies. The relationship between soil quality and fertilizer use should be considered in follow-up study at plot level on nutrient management to assess the possible trade-offs between a nutrient input that is corresponding to plant needs on the long term and negative change in soil quality as acidification (Barak et al., 1997; Lungu and Dynoodt, 2008; Miao et al., 2011; Zhang et al., 2006).

Furthermore, the cross-sectional econometric analysis approach for understanding farmer behavior has a limitation: it can capture only the effects of factors with a particular variation in survey data. For some variables that may affect farmers' fertilizer use that occur equally over the population, e.g., climate or regional policy drivers, the cross-sectional data used cannot yield enough variation for such an empirical analysis. One alternative in follow-up studies would be an econometric analysis with longitudinal data (data collected at multiple points in time) on those variables.

## 4.5 Conclusions

The present study focused firstly on the categorization of farming systems in a hotspot of land degradation in Vietnam. We identified that although almost all households in the study area depended on crop production, some showed a tendency to earn their living from livestock production and off-farm activities (i.e., services, trading), with better income.

Secondly, the findings show how the considerable heterogeneity of farmers' livelihoods can shape farmers' fertilizer use in tropical mountains. The socio-economic factors affecting decisions about fertilizer use were different for different household types. The application of mineral fertilizer in agricultural production in the study area was mainly dependent on demand for food, income, area of farm, and the land available for maize cultivation of each different household type. On the other hand, the area for paddy rice, distance to main market, and household size were the major factors affecting the adoption of manure on a farm. The six household types identified might be used in further studies e.g. for improving nutrient use efficiency and food productivity at farm level.

.

## Appendix A. Supplementary Information

**Table S4.1** Average amounts of fertilizer (water soluble NPK and urea) applied on rice and maize and grain yield in six household types (standard deviation in parentheses)

| | Rice: fertilizer applied (kg/ha)and yield (tons/ha) | | | | | Maize: fertilizer applied (kg/ha)and yield (tons/ha) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *n* | N | $P_2O_5$ | $K_2O$ | Yield | *n* | N | $P_2O_5$ | $K_2O$ | Yield |
| HH type 1 | *62* | 141 (82) | 82 (43) | 25 (13) | 4.6 (1.2) | *64* | 126 (102) | 79 (56) | 24 (17) | 5.2 (2.0) |
| HH type 2 | *42* | 112 (69) | 65 (41) | 19 (12) | 4.9 (1.5) | *53* | 137 (90) | 94 (57) | 28 (17) | 6.2 (1.7) |
| HH type 3 | *27* | 139 (87) | 83 (49) | 25 (15) | 4.8 (1.4) | *46* | 106 (65) | 70 (37) | 21 (11) | 5.6 (1.7) |
| HH type 4 | *7* | 100 (143) | 68 (92) | 20 (28) | 4.6 (1.3) | *9* | 64 (29) | 40 (19) | 12 (6) | 6.3 (1.6) |
| HH type 5 | *2* | 141 (4) | 35 (16) | 11 (5) | 4.3 (2.5) | *4* | 226 (83) | 139 (104) | 42 (32) | 7.4 (1.1) |
| HH type 6 | *3* | 78 (20) | 74 (18) | 22 (5) | 3.7 (2.1) | *3* | 65 (22) | 64 (10) | 19 (3) | 4.4 (2.9) |
| Average | | 129 (82) | 76 (47) | 23 (14) | 4.7 (1.4) | | 122 (88) | 80 (53) | 24 (16) | 5.7 (1.8) |

**Table S4.2** Characteristics of six household types through 9 key socio and economic variables represented for 9 principal components (n=184)

| | Household Type | | | | | |
|---|---|---|---|---|---|---|
| | H1 (n=65) | H2 (n=54) | H3 (n=48) | H4 (n=9 | H5 (n=4) | H6 (n=4) |
| $H_{edu1}$ *(year)* | 7.6 ± 0.6 | 4.3 ± 0.6 | 6.6 ± 0.8 | 4.4 ± 1.5 | 7.3 ± 0.8 | 8 ± 1.8 |
| $H_{size}$ *(person)* | 4.5 ± 0.3 | 5.5 ± 0.5 | 4.2 ± 0.4 | 3.6 ± 1.5 | 5.3 ± 1.5 | 3.3 ± 1.5 |
| $H_{depend}$ | 0.3 ± 0.1 | 0.4 ± 0.1 | 1 ± 0.1 | 0.3 ± 0.3 | 0.3 ± 0.2 | 0.2 ± 0.4 |
| $H_{prodtools}$ *(1000 VND)* | 2757 ± 1022 | 3894 ± 19435 | 1105 ± 490 | 1081 ± 1027 | 55900 ± 40349 | 3513 ± 3012 |
| $H_{land}$ *(m2/person)* | 2585 ± 299 | 2503 ± 317 | 2945 ± 430 | 9551 ± 4288 | 3797 ± 3266 | 2920 ± 5529 |
| $H_{pig}$ *(kg/year)* | 98.6 ± 73.5 | 149.3 ± 82.2 | 36.7 ± 20 | 11.1 ± 17.4 | 11.3 ± 35.8 | 2122.5 ± 1089.4 |
| $H_{cattle}$ *(head)* | 2.9 ± 0.6 | 1.8 ± 0.3 | 1.8 ± 0.4 | 1.8 ± 0.7 | 1 ± 1.3 | 0.8 ± 1.5 |
| $H_{grossincpers}$ *(1000 VND/ person/ year)* | 11600 ± 1337 | 11600 ± 2003 | 12000 ± 2027 | 15200 ± 6371 | 25100 ± 6123 | 40400 ± 45570 |
| $H_{cropincshare}$ *(%)* | 50.8 ± 5.6 | 67.4 ± 6.6 | 59 ± 7.1 | 78.8 ± 11.6 | 44.5 ± 22.9 | 19 ± 29.5 |

The uncertainty range is the confidence interval of the mean at 95% level ($p$ < 0.05).

# 5. Concluding remarks

This study has applied a multilevel framework to assess land degradation from national to farm scale. The main goals of the thesis were:

(1) to differentiate the human-induced land degradation from the climate-driven signals in order to (a) identify and characterize the geographic hotspots of human-induced land degradation and (b) identify the biophysical and socio-economic factors affecting land degradation at national level; and

(2) to understand the diverse social and economic characteristics of households in a degraded hotspot that affect farmers mineral fertilizer and manure use, knowing that the absence of nutrient inputs ineluctably leads on the long term to soil degradation.

This chapter starts by summarizing the research achievements on each topic in the study. The following section presents a general discussion of the findings regarding the scientific achievements and new/emerging questions. Limitations are also indicated regarding the data, methodology, and approaches targeting the research questions (see Chapter 1). Finally, based on the findings, particular implications for improving practices and policies on land management and planning are highlighted, as well as research issues for follow-up studies.

## 5.1 Summary of key findings

The first finding of the present multilevel framework was the identification of hotspots of human-induced land degradation (Chapter 2). The analysis of the biomass productivity trends over the long term (25 years) in the entire country identified an explicit spatial pattern of the most striking places of land degradation, which then served as the basis for other lower-level assessments on land degradation. The human-induced land degradation areas were isolated from climate-driven impacts using the combined results from two methods. About 19% of the national land area (62,592 $km^2$) had been degraded because of anthropogenic factors. The four regions with highly degraded areas consisted of the Northwest, Southeast and Mekong River Delta, Central Highlands, and Central Coast, corresponding to the four regions indicated in the National Action Program (NAP) to combat desertification (2006). These regions were also validated by other approaches to ensure the reliability and consistency of the spatial pattern of land degradation.

The hotspot types of land degradation of the three main land-use zones (i.e., forest zone, agricultural zone, and other unproductive/abandoned lands) give an overview of the relationships between socio-ecological factors and land degradation. The highest area of human-induced land degradation is found on forest land (about 40% of the total degraded area). The agricultural zone and other lands share the remaining areas of land degradation at about 35% and 25%, respectively, of the total degraded area. The four categories of variables used in the cluster analyses include natural constraints, physical and institutional accessibilities, human demography, and economic development status. The analyses differentiated five, six, and five socio-ecological types of degradation hotspots in the forest zone, agricultural zone, and other unproductive/abandoned lands, respectively.

After identifying the hotspots of land degradation on a national scale, the next steps of the assessment framework involved examining which socio-economic and biophysical factors significantly affect the severity and extent of land degradation, as well as how the underlying causes can be interpreted (Chapter 3). The spatial data of human-induced land degradation in Vietnam that were gathered in the first step of the multilevel assessment framework were used for calculating the extent of the province-based degradation and the pixel-based degradation intensity, which are the dependent variables in the cause-effect analyses of land degradation. These analyses were performed for the three major land-use zones (degraded agricultural land, degraded forest land, and unproductive/abandoned land).

A range of social, economic, and biophysical factors were justified as hypothetical causes of the extent and intensity of land degradation. These factors included 6 environmental, 4 demographic, and 6 economic variables. Inferential statistical analyses (i.e., multi-linear regressions and binary logistic regressions) showed that the factors significantly impacting land degradation in all land-use zones included the increase of agricultural production and population density. A higher annual agricultural gross product per capita was likely to increase the extent and intensity of land degradation in all land-use zones. While population is considered an important factor influencing land degradation, its effects differed, due to the specific characteristics of each region. For mountainous areas, the population growth increased the extent of land degradation, but in intensive-cultivation areas in the Red River and Mekong deltas of Vietnam, the increase of population pressure likely reduced land degradation. The effect of environmental factors on land degradation is not likely to be common in all land-use zones. Higher slope, more soil constraint, and farther distance to a road increased the degradation. A neighboring forest was shown to reduce the intensity of land degradation in abandoned, unproductive land. The causation patterns for land degradation were different when examining extent and intensity of land degradation. This differentiation helped identify and interpret the causes of land degradation in a more specific and clearer manner.

One of the most degraded hotspots found at the national level of the first and second steps was selected to carry a study at regional/farm level. The Yen Chau District of Son La Province is located in the Northwest region of Vietnam, where the long-term biomass productivity has seriously declined over a 25-year period. Our stratified-random sampling procedure identified 184 households in the district that were interviewed for collecting the data pertaining to the five assets of the sustainable livelihood framework approach (i.e., social, physical, natural, financial, and human assets) (e.g. see Figure 5.1). These multidimensional household data were then used for identifying the livelihood types of households, thereby accounting for the high social-ecological diversity in the mountain region (Chapter 4). Considering the 22 variables in the household grouping analysis, the study identified six household types with identical livelihood characteristics.

**Figure 5.1** Face-to-face farmer interview to collect information

Household type 1 consisted of 35% of the total surveyed households belonging to three ethnic groups (Thai, Kinh, and Xinh Mun). Low income, more education, and high number of cattle were the main features of this group. Household type 2 also included the Thai, Kinh, and Xinh Mun people, comprising about 29% of the households interviewed. This group was characterized by low education, low income, and little farmland. The households with a high-dependency ratio, lack of labor, and low income were grouped into type 3. Thai people dominated this group, accounting for about 26% of the surveyed households. For these groups, the average gross income per person amounted to around US$550/year (less than US$2/day). Household type 4 consisted of Thai people, who were poor, low educated, and had much land for crop production. Household types 5 and 6 included the better-off households, with their incomes coming mainly from nonfarm activities (type 5) and raising pigs (type 6).

The second step of the household-based study was to identify social and economic determinants of type-specific farmer decisions on the intensity of mineral fertilizer use and manure use. Different household types with specific socioeconomic characteristics resulted in varying practices. The household types with more family members, higher gross income per capita, more land per capita, and larger area of maize tended to use more mineral fertilizer. The higher-dependence ratio of households likely limited mineral fertilizer use. The analyses also indicated that household types with a large size, higher educational level, more dependents, and larger rice fields likely used manure. Households who were farther from the market were less likely to use manure.

## 5.2 General discussion

### 5.2.1 Added values of the proposed multi-level framework for land degradation assessments

Land degradation has occurred in many parts of the world, especially in tropical countries. In the midst of the global issues on land degradation and desertification, assessment of land degradation is necessary at the national level to find where the hotspots of land degradation take place, and at which levels the extent and severity of land degradation occur (Bai et al., 2013). Understanding the causes/drivers of land degradation and considering a wide range of biophysical, social, and economic factors help ensure the success of combating land degradation

(Nkonya et al., 2011a; Oldeman et al., 1991; Vlek et al., 2010). Since land degradation is a complicated process that depends on spatial and temporal aspects and is a consequence of various interactions between human and environmental factors, it is necessary to assess land degradation on different scales/levels.

Chapter 1 stated the general question: How can a multi-scale, land degradation assessment be organized to meet scientific requirements (reliable and comprehensive) and be relevant to stakeholders' needs in mitigating land degradation? As land degradation is a complex process, Geist and Lambin (2004) indicated that in-depth research on the risks of land degradation spanning different scales from the local to the national, regional, and international levels is necessary. Chapter 1 reviewed contemporary methods used for assessing land degradation on different spatial and temporal scales. For example, soil degradation could be assessed by using expert opinions (Oldeman et al., 1991; Stocking and Murnaghan, 2001) on coarse spatial scales, whereas the field measurements method is usually employed for the local level (Sonneveld, 2003; Thiam, 2003). The remote-sensing method with its advantages for multiple spatial and temporal scales has been used recently (Bai et al., 2008b; Gao and Liu, 2008; Metternicht et al., 2010; Vlek et al., 2010; Wessels et al., 2007). Thus, assessment and monitoring attempts on specific scales or levels have been done separately and independently, without information flows linking the assessment work on different scales. Furthermore, quantifying and qualifying the interacting, scale-specific drivers of land degradation have been regarded as challenging tasks (Stringer, 2012). In a Somalian case study, Omuto et al. (2011) suggested a framework for the national assessment of land degradation in drylands by combining time-series, remote-sensing data, and local expert and field observations. However, the framework has potential sources of error; besides the limitation in using coarse spatial resolutions of satellite-driven products, the bias of expert opinions limits the accuracy and consistency of different assessments. For instance, the degradation conditions can be over-estimated for arid environment (Omuto et al., 2011). Reed (2011) proposed a methodological framework that builds on approaches developed by the FAO's LADA project, the World Conservation Approaches and Technologies (WOCAT) program, and the Dryland Development Paradigm (DDP) for the monitoring and assessment of land degradation and sustainable land management. With Reed's approach, combining multiple knowledge sources and types, from local to national and international levels, is recommended. However, the framework seems complicated, and it may not be easily accessible to all stakeholders.

The multilevel framework for land degradation assessment used in this study set different objectives to meet the relevant needs on various scales using data sources available at several levels. The present study integrated three main hierarchical levels of assessment: national, regional, and farm type. At the national level, this work identified the hotspots map of land degradation and the social–ecological types of the hotspots that provided an overview of the issue and information for the next steps (Chapter 2). Four regions were affected, of which the Northwest suffered serious degradation in biomass productivity. The results support national land-use policymakers and planners in targeting better the degraded areas and optimizing national limited budgets to combat land degradation. Based on the results of this chapter, the different environmental, socioeconomic factors in the hotspot regions that were related to the degradation processes were considered as the causes/drivers of land degradation (Chapter 3). The data for these analyses were collected from the relevant national statistics. The potential beneficiaries of this research include policymakers and researchers who are looking for new insights into combating land degradation at macro (national) or meso (regional and provincial) levels. The national assessment provided the geographic foci for conducting assessments at regional and farm-type levels (Chapter 4). At these levels, detailed and grounded data were gathered through surveys. The potential beneficiaries of the findings may be local stakeholders who are seeking farmer group-relevant measures to reduce land degradation.

The multi-level assessment framework used in the study may be adopted and applied for the assessment of land degradation in other countries. For national level, the data used in this assessment are almost free and available. For hotspot/farm level, the data are collected by screening survey which is cost-effective. These advantages of the framework make it applicable for other studies on assessment of land degradation.

The hotspots of human-induced land degradation and the differences of hotspot types in social and ecological conditions that were found in the first assessment (Chapter 2) provided the information for the second assessment in identifying causes/drivers (Chapter 3). The results from those works were the basis for the third assessment at the hotspot/farm level (Chapter 4). On the bottom-up linkages, the qualitative upscale from the hotspot/farm level to the regional and national scales have not been considered. The upscale process can be carried out by aggregating comparable local data from the lower to the upper level or by using biophysical and socioeconomic models (Reed et al., 2011). This work is sensitive to local contexts and would be a potential topic for future studies.

### 5.2.2 Discriminating human-induced degradation signals from the climate-driven ones: New insights and remaining limitation of the used methods

Since land degradation is caused by both natural and anthropologic processes (Von Braun and Gerber, 2012), differentiating human-induced land degradation from climate-driven signals to identify the former's hotspots may help land-use policymakers and planners in combating land degradation. The question is how to do so effectively, based on the available data on the national scale.

Given that the validation of meta-, remotely sensed land degradation assessment is hardly found in current literature, a multi-aspect approach to validate the assessment of the NDVI-based, biomass productivity degradation was used in this study. First, the consistency between the spatial patterns of the inter-annual trends of the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI and the Moderate Resolution Imaging Spectroradiometer (MOD17) NPP was determined by evaluating the overlap area between the trends and calculating the correlation of the inter-annual means. Second, both the Trend-Correlation and ResTrend methods were used to identify the "convergent validity" in discriminating declining human-induced biomass productivity from the climate-driven phenomenon. Third, the assessment results were compared among the four priority regions mentioned in the NAP to Combat Desertification and with those of other reports on deforestation, forest degradation, and agricultural intensification. It was found that these methods yielded consistent and matching results for all the considered analyses.

A challenge of the productivity-based assessment of land degradation is how to account for the huge diversity in the involved social, economic, and biophysical factors to gain adequate understanding of the degradation phenomenon, as well as provide useful implications for development policies (Vlek et al., 2010; Sommer et al., 2011). The social–ecological types of the degradation hotspots were identified based on the relationship between the area of long-term

NDVI decline and a set of socio-ecological variables. This method complemented those of previous studies on the issue, but some important variables such as soil constraints and biophysical and institutional accessibilities were integrated in the analysis. Moreover, the different land-use zones were considered in mapping distinct clusters of degraded pixels. The work offered a feasible way to spatially delineate and characterize the distinct degradation types that are important for formulating further region-specific research.

The findings on the social–ecological hotspots of land degradation across the national scale are necessary for land management planners and policymakers. These hotspot locations may serve as the target areas in combating land degradation. The policy can concentrate on the important region-specific factors suggested by the social–ecological characterization of the degraded hotspots. The four hotspot regions that suffered serious problems need to be targeted by appropriate policies to ensure food security and poverty reduction for the local people, thus reducing pressure on land resources and increasing the carrying capacity of ecosystems (i.e. the size of the population that can be supported indefinitely by an ecosystem without destroying that ecosystem).

Similar to many other NDVI-based land degradation assessments, the method used for the present study has certain limitations. The first limitation is that the linear NDVI trend analysis - similar to those used by many other studies (e.g., Bai et al., 2008b; Helldén and Tottrup, 2008; Wessels et al., 2007) may not be able to capture non-linear NDVI trends that may occur (Wessel et al., 2012). Second, atmospheric fertilization (e.g., elevated $CO_2$ in the air, and the $NH_4$ and $NO_x$ deposition on the land surface) can positively affect vegetation greenness (Buitenwerf et al., 2012; Vlek et al., 2010; Higgins and Scheiter, 2012; Le et al., 2012), thus weakening the actual relationship between NDVI and lands' productivity. This means: NDVI increasing trend is driven by not only the land capacity for biological production, but also external atmospheric fertilization. Similarly, increasing use of fertilizers during the agricultural intensification process in Vietnam's river deltas during the last 20 years (Bo et al., 2003b) may be another important masking effect in our degradation assessment using the NDVI signals. Third, the validation of the NDVI–NPP relationship is still limited to indirect reference NPP data (MODIS NPP) and qualitative judgments using precedent national publications, rather than ground measured data. Due to the lack of temporal vegetation data at national level, the presented study has not considered the effects of changes in vegetation structure (e.g. life-form spectrum and species composition) on the NDVI–NPP relationship (Mbow et al., 2013). Moreover, the relationships between NDVI or NPP trend and other important processes of land degradation (e.g., soil erosion, nutrient mining by prolonged no/low input cultivation) have not yet investigated in this study, thus should be the subject for follow-up studies. Due to the coarse resolution of the NDVI data (8 x 8 $km^2$), the assessment results have a low accuracy. There may be some degraded areas outside of the detected hotspots, and some areas within the hotspots may not be severely degraded. Overcoming this problem requires further verifications in the field and sound knowledge of ground conditions (Foster, 2006). Using finer resolution satellite products (0.5–1-km resolution images) whenever these data are available may also help.

Ground-based surveys or field monitoring to validate the delineated hotspots have not been conducted in this study. Since this work can only be carried out at field or local landscape levels, site selection is important. The hotspots of human-induced land degradation that were found in this study provided explicit spatial patterns and social–ecological types that may serve as the guide for ground-based validations in a systematic and cost-effective way. The effects of changes in vegetation structure on the NDVI–NPP relationship have not been examined. This work requires detailed vegetation data that can be collected in follow-up studies on finer scales (farm, field, or watershed levels). The use of global data on soil constraints (GAEZ) for spatially-explicit national assessment is also a limitation of the study. As indicated in the project website (http://webarchive.iiasa.ac.at/Research/LUC/GAEZ/index.htm), the quality and reliability of datasets are known to be uneven across regions. However, given there is no national data on soil constraints, there is no other options than GAEZ. Therefore, the future investment on qualified spatial soil database across the nation will be one of the data bases for obtaining more correct assessment results.

### 5.2.3 The biophysical and socio-economic causes of land degradation: contextualization of the empirical findings and used methods, and policy implications

In line with previous works (see Nkonya et al., 2011a; Vogt et al., 2011), this study showed that human activities are the main causes of soil degradation, and the human-induced degradation is accelerated by unfavorable environmental conditions (e.g., steep land, low to very low nutrient contents in many soil types in the tropics, droughts, or heavy rains). Population pressure is an important factor that needs to be considered in specific contexts. Although some previous studies also obtained such findings, they did not clarify the contexts and related causalities (Scherr et al., 1995; von Braun et al., 2012), as was done in this research. We suggest that population pressure will be an issue for lands with low carrying capacities (e.g., tropical mountains and hillsides) serving as frontiers for extensive agrarian communities. Increased population pressure in an extensive agrarian society in the mountains forces farmers to shorten or cancel fallow periods, leading to rapid soil degradation. Rural population growth also increases the likelihood that forested regions will be transformed, reduced, or burned for extractive processes or extensive agricultural production. These findings are consistent with those of Grepperud (1996), whose study was carried out in Ethiopia's marginal areas. However, Boserup's (1965) hypothesis likely remains valid in crowded cultivation areas such as the Red River Delta. Increased population pressure with the conditions of improved market access and extension services can motivate farmers to be innovative and invest in different forms of intensified farming practices that can bring about crop production on infertile land. In this case, the increases of population pressure were likely to decrease land degradation in intensive cultivation areas.

Previous studies to determine the causes/drivers of land degradation mainly focused on the socio-economic factors on global and regional scales (e.g., Bai et al., 2008b; Vlek et al., 2008, 2010) or the national scale (Barbier, 1997). Some studies have considered the correlation between land degradation and some natural factors and land-use management practices on the national and subnational scales, but without appropriate inferential analyses. The methods and approaches employed in the present study have filled these gaps.

A number of new features characterized the way the cause-effect analyses were performed in this study, compared to those of preceding studies. First, the two dimensions (i.e., extent and intensity) of the severity of land degradation were used. Previous studies only identified the determinants of either the intensity (Nkonya et al., 2011a) or the spatial extent of degradation

(DeFries et al., 2010; Jorgenson and Burns, 2007; Reddy, 2003). Considering two facets of land degradation can make the causal analysis more specific and clearer in interpreting the causes/drivers of the phenomenon. Second, the degradation causes in the land-use context were identified by examining separate, major land-use types. As recommended by previous studies, defined strata of land-use regimes should be used in causal analyses of land degradation. Thus, the results of the causation pattern for each land-use zone can provide new insights for national policies on combating land degradation. Third, this study included both natural and anthropogenic factors and applied the causal analyses of land degradation. The biophysical variables (i.e., slope, soil constraints, distance to road and market, and abundance of forest and agriculture within the neighborhoods of the considered locations) were not analyzed in previous studies. The inferential statistical methods complemented by both multiple linear regression analysis and binary logistic regression are likely effective in detecting and understanding land degradation causes at the national level.

Data quality is also critical in such analyses. While the environmental data were extracted from spatial data sources, the socioeconomic data were taken from national statistics for the provincial level. These data were integrated with the administrative polygon map, then converted from polygon-based to pixel-based data to nest with the land degradation and other environmental data. Using this data may cause uncertainties in the results (Chapter 3). Data on lower scales (district/commune) would need to be more accurate. However, this work is likely impractical and unfeasible for the whole country. The socio-economic data at district/commune levels are only available for a specific area, which cannot be generalized upper levels (regional/national levels).

### 5.2.4 Household-farm type-specific causal patterns in fertilizer investment and adoption decisions: new methodological insights and implications for effective mountainous agricultural policies

The results of the present study show the importance of smallholder farms types in shaping farmers' behavioral patterns regarding fertilizer and manure uses. In other words, given the same set of factors affecting farmer decisions, the magnitudes and directions of the factors' impacts can differ among household-farm types. This finding is consistent with those of studies in other countries (Fufa and Hassan, 2006; Waithaka et al., 2007; Olayide et al., 2009; Zhou et al., 2010; Adhikari, 2011). The basis for this response/behavior diversity of farmer decisions on fertilizer uses can not only be the difference between resource constraints and opportunities among livelihood groups (objective basis), but also the difference in personal preferences, beliefs, perceptions, and satisfaction levels (value basis) among groups (e.g., see Duflo et al., 2009). The important role of response/behavior diversity in fertilizer decision and adaption analysis implies two important points. First, given a target community, it is necessary to define the relevant livelihood typology and based on it, identify livelihood types to understand type-specific, cause-effect relationships between drivers and fertilizer use decision/adoption. Second, understanding household typology and household type-specific behavior regarding fertilizer use should be useful for informing effective agricultural policy, since sound policy measures need to be as explicit as possible to remove constraints, promote opportunities, and recognize local preferences, which are all specific for livelihood groups (Laurent et al., 1999).

The approach and methods of the present study have some limitations. First, instead of considering the total amount of N, P, and K fertilizers used as the dependent variable, the input and input-output balance should be analyzed for each element. Second, some additional potential explanatory factors can be used in the analyses such as ethnicity, institution/policy, and human attitudes. Further studies using these variables sould be undertaken. Third, the analyses in this study did not include soil properties, which are directly related to soil and land degradation (Norton et al., 1996). Because each farmer in the research area usually owns many plots distributed among different locations, the soil properties is difficult to collect and measure. Follow-up studies on the plot/field level should be pursued to overcome this limitation. Fourth, the limitation of the cross-sectional, econometric analysis approach used in this study was also indicated, since it was difficult to measure the influences of some factors that showed a little variation (e.g., policy and climate). Using longitudinal data on such variables in analyzing or obtaining direct information from farmers through hypothetical and ranking questions could be helpful.

## 5.3 Suggestive issues for further research

Further research using the direct indicators of land degradation on different scales can be used to clarify specific land degradation processes, such as deforestation and forest degradation, soil erosion and nutrient depletion. For instance, soil nutrient balance could be an indicator of land degradation/improvement at the regional and farm levels (Cobo et al., 2010; Hoang and Alauddin, 2010; Hoang and Nguyen, 2013). Correct and comprehensive assessment of nutrient balance requires for research on involved processes such as soil erosion/deposition, crop-soil nutrient dynamics, nutrient flows within and between farms, and impacts of farm management practices on the nutrient stocks and flows. The degraded hotspots could be studied in depth by using other indicators and ground-truth evidences to verify the results at the national level. These validations should be done at the field or local landscape levels for the defined hotspots.

**Figure 5.2** Upland fields for maize cultivation without conservation measures in Yen Chau District, Son La Province, in the Northwest degradation hotspot. The pictures were taken during the fallow period, showing the soil exposed to wind and rainfall.

The approach of the multilevel assessment of land degradation in this study responded to a genuine need and was consistent with Reed et al.'s (2011) suggestion, which mentioned that multiple knowledge sources and types from local to national and international scales should be incorporated into the framework of cross-scale monitoring and assessment of land degradation. Further studies following the multilevel assessment framework to integrate scientific and indigenous knowledge might serve effectively in combating the land degradation and desertification for a specific region. Methods for scaling site-specific results (i.e., at the detailed watershed or farm scale) up to broader scales needs to be studied further.

The next study using modeling approach in assessing nutrient balances and analyzing farm nutrient flows should be carried out for different smallholder household types in the upland area of Vietnam. Using a dynamic socio-ecological system model to monitor and calculate nutrient flows seems to be a potential approach to capture the changes of farming systems over time and space. A comprehensive nutrient flows analysis for the whole farm, such as many studies reviewed by Cobo et al. (2010), can assess soil nutrient balance, and nutrient use efficiencies of different production units within farm, as well as the whole farm. Furthermore, this approach allows doing different sensitivity analyses of modeled farm nutrient flows to know what key processes (e.g., soil erosion, or nutrient mining by crops, or inappropriate fertilizer management practices) causing decline in soil nutrients.

The dynamic relation between climate change and land degradation is complicated and should be examined in future research. Investigating the impacts of climate change on land and soil is a difficult task, because they may differ according to specific conditions (Cooke and Toda, 2008). Climate anomalies (i.e., the La Niña/El Niño phenomena, sea level rise, abnormal typhoons, droughts, and floods) are factors that should be specially considered, since they can have strong influences on processes of land degradation. For example, the concentration of heavy rains within a short period can cause severe soil erosion on mountainous areas compared to years with ambient monthly rainfalls. A prolonged drought in a year or repeating droughts in a number of years can reduce significantly water availability over large region, thus limiting the growth of natural vegetation and rain-fed crops.

Developing a user-friendly and easily accessible tool based on geographic information systems (GIS) can be part of future work to effectively combat land degradation. This interaction tool will be used to integrate and assemble updated data on land resources to help stakeholders understand the status of the land, analyze the trends, and make decisions based on the information. The tool can also consist of appropriate technologies for land degradation alleviation and soil conservation measures to provide necessary information for various stakeholders at different levels. Local experts might be able to upload related data and create different scenarios to find solutions based on human and environmental interactions involving land degradation.

## Acknowledgments

This thesis would not have been possible without the support of so many people.

I thank Emmanuel Frossard for taking over the supervision of this thesis due to professorship changes at the Natural and Social Science Interface (NSSI). He provided me with appreciative feedback on my work and freedom of research. I received a warm welcome from his research group, the Plant Nutrition Group (IAS), and had an opportunity to present my research and receive valuable comments.

I also express my gratitude to Paul L.G. Vlek, my co-supervisor. At the beginning of my doctoral study at the Center for Development Research (ZEF) (University of Bonn), he accepted me as a PhD candidate and supervised me in my formulation of the research proposal on land degradation—a challenging but interesting topic. His prompt responses with valuable comments, suggestions during the course of my dissertation writing, as well as constant encouragement are always greatly appreciated.

Thanks are also conveyed to my ex-supervisor Roland W Scholz, who accepted the transition of my doctoral study from the University of Bonn to ETH Zurich, and kindly supervised me from November 2010 to July 2012.

Furthermore, special thanks go to Quang Bao Le, my co-supervisor. During all the time we worked together, he enthusiastically shared with me his in-depth knowledge and many great ideas in land resource management, sustainable agriculture, as well as his skills in GIS, remote sensing, and statistics. He helped me a lot not only in the research but also in life abroad. Moreover, during our time in Switzerland, Bao and his wife Phuong welcomed me as a family member, invited me to enjoy delicious Vietnamese dishes almost every weekend, and shared many happy moments. I really appreciate it and will never forget such a great time.

I thank Michael Stauffacher and Pius Krütli for their extensive support for this PhD over the last two years and helpful feedback on my manuscript. Their time, interest, and support are greatly appreciated. I extend my thanks to Rainer Schulin, who agreed to serve on the committee with an external review of this thesis.

During my research, I had the opportunity to work in two well-known organizations the Center for Development Research (ZEF) at the University of Bonn and Natural and Social Science Interface (NSSI) at ETH Zurich. Wherever I worked, I met many impressive colleagues who were always willing to share their work and life experiences. I thank all colleagues at ZEF and the NSSI for the many good moments we had together over lunch, coffee or beer, at picnics and parties, and for offering such a diverse, inspiring, and supportive working environment. At ZEF, I am especially grateful to Guenther Manske, Rosemarie Zabel, Sabine Aengenendt-Baer, and Doris Fuß for their support during the first two years of my research. At the NSSI, I appreciate the administrative and computer support of Maria Rey, Andy Aragai and Sandro Bösch-Pauli. My gratitude goes to Laura de Braun, Gregoire Meylan, and Andrea Ulrich for their valuable comments on the earlier drafts of my papers. Special thanks are also extended to my supervisors and NSSI colleagues for their support and encouragement during the interruption of my studies due to the unexpected situation with my daughter. On behalf of my family, I really appreciate your kindness.

I'm also grateful to Nguyen Xuan Lai, Tran Minh Tien, and other colleagues at the Soils and Fertilizers Research Institute (SFRI), Vietnam for their support and unconditional help when needed. I thank the many households in Yen Chau District, Son La Province for taking part in my survey and being always positive and supportive. I appreciate my close Vietnamese friends in Zurich and Bonn who shared with me the life abroad with much fun and relaxation.

I could not have implemented all the above-mentioned tasks without the financial support from the Agricultural Science and Technology Project (AST) under the Ministry of Agriculture and Rural Development (MARD) of Vietnam. This support is gratefully acknowledged, providing me with the opportunity to live in the beautiful countries of Germany and Switzerland and meet people from many nations. I thank Pham Hung, Nguyen The Hinh, Tran Thi Anh Thu, Thuy Linh, and others for their support on administrative and financial procedures. Additionally, my research was funded by the NSSI (six months) and the ETH Doctoral Scholarship (three months) at the final stage, which I sincerely appreciate.

For many people, leaving their elderly parents, lonely spouse, and beloved children behind to study abroad for some time is extremely difficult and may seem challenging. This was exactly what I experienced when I lived in Bonn and Zurich. However, it strengthened me to give my best efforts, because I knew that far away in Vietnam, my extended family was looking forward to my success and our reunion. I would like to send my thanks with love and appreciation to my parents, parents-in-law, siblings, and friends for their great support and unconditional love.

Above all, I express my deepest thanks to my wife Tran Thi Thu Thuy who took care of our two lovely children during my studies abroad. Living in Vietnam in my absence was a hard time for my wife and my children. I dedicate this thesis to my wife, my ten-year-old daughter Vu Tran Minh Trang, and my three-year-old son Vu Duc Minh.

Manh Quyet Vu

Zurich, May 2014

## References

Abbasi, M.K., Zafar, M., Khan, S., 2007. Influence of different land-cover types on the changes of selected soil properties in the mountain region of Rawalakot Azad Jammu and Kashmir. Nutrient Cycling in Agroecosystems 78, 97-110.

Abu, S.T., 2013. Evaluating long-term impact of land use on selected soil physical quality indicators. Soil Research 51, 471-476.

Adhikari, D., 2011. Factors Affecting Farmer's Decision to Use Fertilizer: An Event History Modelling Approach.

Akpan, S.B., Aya, E.A., 2009. Determinants of fertilizer use among small - holder farmers in Wetland Region of Cross River State. Global Journal of Agricultural Sciences 8, 195-201.

Alessa, L., Kliskey, A., Brown, G., 2008. Social–ecological hotspots mapping: A spatial approach for identifying coupled social–ecological space. Landscape and Urban Planning 85, 27-39.

Ali, M., 2002. The vegetable sector in Indochina countries: A synthesis, in: Ali, M. (Ed.), The Vegetable Sector in Indochina Countries: Farm and Household Perspectives on Poverty Alleviation. Asian Regional Center (ARC, Thailand) and Asian Vegetable Research and Development Center (AVRDC, Taiwan), Taiwan, pp. 1-31.

Amanze, B., Eze, C.C., Eze, V., 2010. Factors Influencing the Use of Fertilizer in Arable Crop Production Among Smallholder Farmers In Owerri Agricultural Zone of Imo State. Academia Arena 2 (6), 90-96.

Angelsen, A., 1996. Deforestation: Population or market driven? Different approaches in modeling of agricultural expansion. Chr. Michelsen Institute (CMI), Bergen.

Anh, D.N., Tacoli, C., Hoang, T.X., 2003. Migration in Vietnam: A review of information on current trends and patterns, and their policy implications, Paper presented at the Regional Conference on “Migration, Development and Pro-Poor Policy Choices in Asia”, 22–24 June 2003, Dhaka, Bangladesh.

Anselin, L., 2001. Spatial Econometrics, in: Baltagi, B.H. (Ed.), A Companion to Theoretical Econometrics. Blackwell Scientific Publications, Oxford, U.K, pp. 310-330.

Aregay, F.A., Minjuan, Z., 2012. Impact of Irrigation on Fertilizer Use Decision of Farmers in China: A Case Study in Weihe River Basin. Journal of Sustainable Development 5, 74-82.

Ashley, C., Carney, D., 1999. Sustainable Livelihoods: Lessons from Early Experience. Department for International Development, (DFID), London, UK

Asrar, G., Fuchs, M., Kanemasu, E.T., Hatfield, J.L., 1984. Estimating absorbed photosynthetic radiation and Leaf Area Index from spectral reflectance in wheat. Agron. J 76, 300-306.

Ayoub, A.T., 1998. Extent, severity and causative factors of land degradation in the Sudan. Journal of Arid Environments 38, 397-409.

Bader, M.Y., Ruijten, J.J.A., 2008. A topography-based model of forest cover at the alpine tree line in the tropical Andes. Journal of Biogeography 35, 711-723.

Bai, Z., Dent, D., Wu, Y., Jong, R., 2013. Land Degradation and Ecosystem Services, in: Lal, R., Lorenz, K., Hüttl, R.F., Schneider, B.U., von Braun, J. (Eds.), Ecosystem Services and Carbon Sequestration in the Biosphere. Springer Netherlands, pp. 357-381.

Bai, Z.G., Dent, D.L., Olsson, L., Schaepman, M.E., 2008a. Global Assessment of Land Degradation and Improvement 1. Identification by remote sensing. ISRIC - World Soil Information, Food and Agriculture Organization of The United Nations.

Bai, Z.G., Dent, D.L., Olsson, L., Schaepman, M.E., 2008b. Proxy global assessment of land degradation. Soil Use and Management 24, 223-234.

Barak, P., Jobe, B., Krueger, A., Peterson, L., Laird, D., 1997. Effects of long-term soil acidification due to nitrogen fertilizer inputs in Wisconsin. Plant and Soil 197, 61-69.

Barbier, E.B., 1997. The economic determinants of land degradation in developing countries. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences 352, 891-899.

Bebbington, A., 1999. Capitals and Capabilities: A Framework for Analyzing Peasant Viability, Rural Livelihoods and Poverty. World Development 27, 2021-2044.

Bo, N., V, 2013. Improving fertilizer use efficiency for crops in Vietnam National conference on fertilizer, Can Tho, Vietnam, pp. 13-42.

Bo, N.V., Mutert, E., Sat, C.D., 2003a. BALCROP: Balanced Fertilization for Better Crops in Vietnam. Potash and Phosphate Institute/Potash and Phosphate Institute of Canada (Southeast Asia Programs).

Bo, N.V., Thi, N.T., Hien, B.H., Chien, N.V., 2003b. Balanced Fertilizer Application for Crops in Vietnam, from Theory to Practice. [in Vietnamese]. Agricultural Publishing House, Ha Noi.

Boserup, E., 1965. The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure. London: G. Allen and Unwin. Chicago: Aldine.

Bradley, P.S., Fayyad, U.M., 1998. Refining Initial Points for K-Means Clustering, Proceedings of the Fifteenth International Conference on Machine Learning. Morgan Kaufmann Publishers Inc., Madison, Wisconsin, USA, pp. 91-99.

Brown, M.E., Pinzon, J.E., Tucker, C.J., 2003. Quantitative Comparison of Four AVHRR Global Data Sets for Land Applications. Greenbelt, MD, Global Mapping and Modelling Systems (GIMMS). under review: 35.

Buitenwerf, R., Bond, W.J., Stevens, N., Trollope, W.S.W., 2012. Increased tree densities in South African savannas: >50 years of data suggests CO2 as a driver. Global Change Biology 18, 675-684.

Cardille, J.A., Bennett, E.M., 2010. Ecology: Tropical teleconnections. Nature Geosci 3, 154-155.

Carlson, T.N., Ripley, D.A., 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment 62, 241-252.

Carney, D., 1998. Sustainable Rural Livelihoods: What Contribution Can We Make? Department for International Development, London.

Castella, J.C., Hoa, T.Q., Husson, O., Nam, V.H., Quang, D.D., 2002. The declining role of ethnicity in farm household differentiation: a case study from Ngoc Phai Commune, Cho Don District, Bac Kan Provience, Viet Nam, in: Castella, J.C., Quang, D.D. (Eds.), Doi Moi in the mountains : Land use changes and farmers' livelihood strategies in Bac Kan Province, Viet Nam. The Agricultural Publishing House, Hanoi, pp. 47-71.

Chen, S., Rao, P., 2008. Land degradation monitoring using multi-temporal Landsat TM/ETM data in a transition zone between grassland and cropland of northeast China. International Journal of Remote Sensing 29, 2055 - 2073.

Chien, S.H., Prochnow, L.I., Cantarella, H., 2009. Recent Developments of Fertilizer Production and Use to Improve Nutrient Efficiency and Minimize Environmental Impacts, in: Donald, L.S. (Ed.), Advances in Agronomy. Academic Press, pp. 267-322.

Chouichom, S., Yamao, M., 2011. Organic Fertilizer Use in Northeastern Thailand: An Analysis of Some Factors Affecting Farmers’ Attitudes, in: Behnassi, M., Shahid, S.A., D'Silva, J. (Eds.), Sustainable Agricultural Development. Springer Netherlands, pp. 185-196.

Clement, F., Amezaga, J.M., 2009. Afforestation and forestry land allocation in northern Vietnam: Analysing the gap between policy intentions and outcomes. Land Use Policy 26, 458-470.

Cobo, J.G., Dercon, G., Cadisch, G., 2010. Nutrient balances in African land use systems across different spatial scales: A review of approaches, challenges and progress. Agriculture, Ecosystems & Environment 136, 1-15.

Cooke, R., Toda, A., 2008. Confronting Climate Change and Land Degradation in Viet Nam: Increasing Finance for Sustainable Land Management. Global Mechanism of the UNCCD 2008.

Cozzolino, D., Moron, A., 2003. The potential of near-infrared reflectance spectroscopy to analyse soil chemical and physical characteristics. The Journal of Agricultural Science 140, 65-71.

Dang, M.V., 2005. Soil–plant nutrient balance of tea crops in the northern mountainous region, Vietnam. Agriculture, Ecosystems & Environment 105, 413-418.

de Jong, R., de Bruin, S., de Wit, A., Schaepman, M.E., Dent, D.L., 2011. Analysis of monotonic greening and browning trends from global NDVI time-series. Remote Sensing of Environment 115, 692-702.

de Jong, R., Verbesselt, J., Schaepman, M.E., de Bruin, S., 2012. Trend changes in global greening and browning: contribution of short-term trends to longer-term change. Global Change Biology 18, 642-655.

De Koninck, R., 1999. Deforestation in Vietnam. International Development Research Centre (IDRC), Ottawa, Canada.

de Koning, G.H.J., Verburg, P.H., Veldkamp, A., Fresco, L.O., 1999. Multi-scale modelling of land use change dynamics in Ecuador. Agricultural Systems 61, 77-93.

De, N.V., Douglas, I.A.N., McMorrow, J., Lindley, S., Thuy Binh, D.K.N., Van, T.T., Thanh, L.H., Tho, N., 2008. Erosion and nutrient loss on sloping land under intense cultivation in southern Vietnam. Geographical Research 46, 4-16.

De Pinto, A., Nelson, G.C., 2002. Correcting for spatial effects in limited dependent variable regression: assessing the value of "Ad-hoc" techniques. . American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

DeFries, R.S., Rudel, T., Uriarte, M., Hansen, M., 2010. Deforestation driven by urban population growth and agricultural trade in the twenty-first century. Nature Geosci 3, 178-181.

Douglas, I.A.N., 2006. The local drivers of land degradation in South-East Asia. Geographical Research 44, 123-134.

Duflo, E., Kremer, M., Robinson, J., 2009. Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. National Bureau of Economic Research Working Paper Series No. 15131.

Dung, N.V., Vien, T.D., Lam, N.T., Tuong, T.M., Cadisch, G., 2008. Analysis of the sustainability within the composite swidden agroecosystem in northern Vietnam: 1. Partial nutrient balances and recovery times of upland fields. Agriculture, Ecosystems & Environment 128, 37-51.

Duong, N.V., 2004. Land cover mapping of Vietnam using MODIS 500m 32-day global composites, International Symposium on Geoinformatics for Spatial Infrastructure Development in Earth and Allied Sciences, Hanoi, Vietnam, pp. 1-6.

Eswaran, H., Lal, R., Reich, P.F., 2001. Land Degradation: An overview, in: Bridges, E.M., Hannam, I.D., Oldeman, L.R., Pening de Vries, F.W.T., Scherr, S.J., Sompatpanit , S. (Eds.), Responses to Land Degradation Responses to Land Degradation ed. Oxford Press, New Delhi, India, Khon Kaen, Thailand.

Evans, J., Geerken, R., 2004. Discrimination between climate and human-induced dryland degradation. Journal of Arid Environments 57, 535-554.

FAO, 1999. The Future of Our Land - Facing the Challenge, Rome.

FAO, 2000. Land resource potential and constraints at regional and country levels, World Soil Resources Reports 90, FAO, Land and Water Development Division, Rome, 114 p. www.fao.org/ag/agl/agll/terrastat.

FAO, 2010. Global Forest Resources Assessment 2010, Main report, FAO Forestry Paper 163, Rome.

Fatoux, C., Castella, J.C., Zeiss, M., Manh, P.H., 2002. From rice cultivator to agroforester within a decade: The impact of Doi Moi on agricultural diversification in a mountainous commune of Choi Moi District, Backan Province, Viet Nam, in: Castella, J.C., Quang, D.D. (Eds.), Doi Moi in the Mountains: Land use Changes and Farmers' Livelihood Strategies in Bac Kan Province, Viet Nam. The Agricultural Publishing House, Hanoi, pp. 73-98.

Fensholt, R., Langanke, T., Rasmussen, K., Reenberg, A., Prince, S.D., Tucker, C., Scholes, R.J., Le, Q.B., Bondeau, A., Eastman, R., Epstein, H., Gaughan, A.E., Hellden, U., Mbow, C., Olsson, L., Paruelo, J., Schweitzer, C., Seaquist, J., Wessels, K., 2012. Greenness in semi-arid areas across the globe 1981–2007 — an Earth Observing Satellite based analysis of trends and drivers. Remote Sensing of Environment 121, 144-158.

Fensholt, R., Rasmussen, K., Nielsen, T.T., Mbow, C., 2009. Evaluation of earth observation based long term vegetation trends -- Intercomparing NDVI time series trend analysis consistency of Sahel from AVHRR GIMMS, Terra MODIS and SPOT VGT data. Remote Sensing of Environment 113, 1886-1898.

Fischer, G., F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, Wiberg, D., 2008. Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008). IIASA Laxenburg, Austria and FAO, Rome, Italy.

Fischer, G., van Velthuizen, H.T., Shah, M., Nachtergaele, F.O., 2002. Global Agro-ecological Assessment for Agriculture in the 21st Century: Methodology and Results. International Institute for Applied Systems Analysis (IIASA) and Food and Agriculture Organization of the United Nations (FAO), Laxenburg, Austria.

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

FORRU, 2008. Research for Restoring Tropical Forest Ecosystems: A Practical Guide. Forest Restoration Research Unit, Biology Department, Science Faculty, Chiang Mai University, Thailand.

Foster, R.H., 2006. Methods for assessing land degradation in Botswana. Earth & E-nvironment 1, 238-276.

Fox, J., Kanter, R., Yarnasarn, S., Ekasingh, M., Jones, R., 1994. Farmer decision making and spatial variables in northern Thailand. Environmental Management 18, 391-399.

Frossard, E., Bünemann, E., Jansa, J., Oberson, A., Feller, C., 2009. Concepts and practices of nutrient management in agro-ecosystems: Can we draw lessons from history to design future sustainable agricultural production systems? Die Bodenkultur 60, 43-60.

Fufa, B., Hassan, R.M., 2006. Determinants of fertilizer use on maize in Eastern Ethiopia: A weighted endogenous sampling analysis of the extent and intensity of adoption. Agrekon 45.

Gao, J., Liu, Y., 2008. Mapping of land degradation from space: a comparative study of Landsat ETM+ and ASTER data. International Journal of Remote Sensing 29, 4029 - 4043.

GEF, 2006. Land degradation as a global environmental issue: a synthesis of three studies commissioned by the global environment facility to strengthen the knowledge base to support the land degradation focal area. Global Environment Facility, Washington, DC.

Geist, H., Lambin, E., 2002. Proximate causes and underlying driving forces of tropical deforestation. BioScience 52, 143-150.

Geist, H.J., Lambin, E.F., 2004. Dynamic causal patterns of desertification. BioScience 54, 817-829.

Godoy, R.A., 2001. Indians, Markets and Rainforests: Theory, Methods, Analysis. Columbia University Press, New York.

Greene, W.H., 2012. Econometric Ananysis (7th edition). Prentice Hall, Boston, USA.

Grepperud, S., 1996. Population pressure and land degradation: The case of Ethiopia. Journal of Environmental Economics and Management 30, 18-33.

GSO, 2009. Statistical Year Book of Vietnam, General Statistics Office. Statistical Publishing House, Hanoi, Vietnam.

GSO, 2010. Statistical Year Book of Vietnam, General Statistics Office. Statistical Publishing House, Hanoi, Vietnam.

GSO, 2012. Statistical Year Book of Vietnam, General Statistics Office. Statistical Publishing House, Hanoi, Vietnam.

Ha, D.T., Thao, T.D., Khiem, N.T., Trieu, M.X., Gerpacio, R.V., Pingali, P.L., 2004. Maize in Vietnam: Production Systems, Constraints, and Research Priorities. CIMMYT: International Maize and Wheat Improvement Center.

Ha, N.T., 1996. Determining the factors causing erosion and the capability to forecast erosion on sloping land. PhD dissertation. University of Water Resources, Ha Noi.

Heffer, P., 2013. Assessment of Fertilizer Use by Crop at the Global Level 2010-2010/11. International Fertilizer Industry Association (IFA), Paris.

Helldén, U., Tottrup, C., 2008. Regional desertification: A global synthesis. Global and Planetary Change 64, 169-176.

Herrmann, S.M., Anyamba, A., Tucker, C.J., 2005. Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. Global Environmental Change Part A 15, 394-404.

Higgins, S.I., Scheiter, S., 2012. Atmospheric CO2 forces abrupt vegetation shifts locally, but not globally. Nature 488, 209-212.

Hoang, V.-N., Alauddin, M., 2010. Assessing the eco-environmental performance of agricultural production in OECD countries: the use of nitrogen flows and balance. Nutrient Cycling in Agroecosystems 87, 353-368.

Hoang, V.-N., Nguyen, T.T., 2013. Analysis of environmental efficiency variations: A nutrient balance approach. Ecological Economics 86, 37-46.

Hoang, X.T., Truong, T.A., Luu, T.Q., Dinh, T.G., Dinh, T.T.P., 2013. Food security in the context of Vietnam's rural – urban linkages and climate change. IIED Country Report. IIED, London.

Hosmer, D.W., Lemeshow, S., 2000. Applied Logistic Regression (2nd edition). John Wiley & Sons, New York, USA.

Hossain, M., Singh, V.P., 2000. Fertilizer use in Asian agriculture: implications for sustaining food security and the environment. Nutrient Cycling in Agroecosystems 57, 155-169.

Howeler, R.H., Phien, T., 2000. Integrated nutrient management for more sustainable cassava production in Vietnam, Proceedings of the Vietnamese Cassava Workshop on Progress in Cassava Research and Extension in Vietnam, Ho Chi Minh city, Vietnam, pp. 12-54.

Hung, N.T., 2001. Soil erosion by rain; its effect on soil fertility and crop yield. Agriculture and Rural Development Monthly Journal 5, 334-335.

Huxman, T.E., Smith, M.D., Fay, P.A., Knapp, A.K., Shaw, M.R., Loik, M.E., Smith, S.D., Tissue, D.T., Zak, J.C., Weltzin, J.F., Pockman, W.T., Sala, O.E., Haddad, B.M., Harte, J., Koch, G.W., Schwinning, S., Small, E.E., Williams, D.G., 2004. Convergence across biomes to a common rain-use efficiency. Nature 429, 651-654.

Jabbar, M.T., Chen, X., 2006. Land degradation assessment with the aid of geo-information techniques. Earth Surface Processes and Landforms 31, 777-784.

Jamieson, N.L., Le, T.C., Rambo, A.T., 1998. The development crisis in Vietnam's mountains. East–West Center, Honolulu, Hawaii, USA.

Jansa, J., Frossard, E., Stamp, P., Kreuzer, M., Scholz, R.W., 2010. Future Food Production as Interplay of Natural Resources, Technology, and Human Society. Journal of Industrial Ecology 14, 874-877.

Jorgenson, A.K., 2006. Unequal ecological exchange and environmental degradation: A theoretical proposition and cross-national study of deforestation, 1990–2000*. Rural Sociology 71, 685-712.

Jorgenson, A.K., Burns, T.J., 2007. Effects of rural and urban population dynamics and national development on deforestation in less-developed countries, 1990–2000*. Sociological Inquiry 77, 460-482.

Jorgenson, A.K., Dick, C., Shandra, J.M., 2011. World economy, world society, and environmental harms in less-developed countries*. Sociological Inquiry 81, 53-87.

Jorgenson, A.K., Kuykendall, K.A., 2008. Globalization, Foreign Investment Dependence and Agriculture Production: Pesticide and Fertilizer Use in Less-developed Countries, 1990–2000. Social Forces 87, 529-560.

Kaimowitz, D., Angelsen, A., 1998. Economic models of tropical deforestation: a review. CIFOR, Bogor, Indonesia.

Karanja, D.D., Jayne, T.S., Strasberg, P., 1998. Maize Productivity and Impact of Market Liberalization in Kenya. Tegemeo Working Paper. Tegemeo Institute, Egerton University, Nairobi.

Keil, A., Saint-Macary, C., Zeller, M., 2008. Maize boom in the uplands of Northern Vietnam : economic importance and environmental implications. Universitaet Hohenheim, Department of Agricultural Economics and Social Sciences in the Tropics and Subtropics.

Kham, D.V., Giang, B.D., Thu, C.M., Huyen, N.T., 2007. Use of multi-date remote sensing data to evaluate vegetation indices changes of the land cover and some analysis of crop and rice state in Red River and Cuu Long River delta. Report at Scientific conference 10th of Institute of Meteorology, Hydrology and Environment. Link: http://www.imh.ac.vn/b_tintuc_sukien/bc_hoinghi_hoithao/L555-thumuccuoi/mlfolder.2007-04-13.0236405440/24%20DVKham2.pdf accessed on 03 Jan 2010.

Kherallah, M., Minot, N., Kachule, R., Soule, B.G., Philippe, Berry, 2001. Impact of Agricultural Market Reforms on Smallholder Farmers in Benin and Malawi, Final report. International Food Policy Research Institute, Wasington DC.

Kintigh, K.W., Ammermann, A.J., 1982. Heuristic Approaches to Spatial Analysis in Archaeology. American Antiquity 47, 31-63.

Koerner, C., Ohsawa, M., 2005. Mountain systems, in: Hassan, R., Scholes, R., Ash, N. (Eds.), Ecosystems and Human Well-being: Current State and Trends. Island Press, Washsington DC, pp. 681-716.

Lal, R., Safriel, U., Boer, B., 2012. Zero Net Land Degradation: A New Sustainable Development Goal for Rio+ 20. Secretariat of the United Nations Convention to Combat Desertification (UNCCD), pp. 1-30. http://www.unccd.int/Lists/SiteDocumentLibrary/secretariat/2012/Zero%2020Net%2020Land%2020Degradation%2020Report%2020UNCCD%2020May%202012%202020background.pdf (accessed on August 202013).

Lam, N.T., Patanothai, A., Limpinuntana, V., Vityakon, P., 2005. Land-Use Sustainability of Composite Swiddening in the Uplands of Northern Vietnam: Nutrient Balances of Swidden Fields during the Cropping Period and Changes of Soil Nutrients over the Swidden Cycle. International Journal of Agricultural Sustainability 3, 57-68.

Lambin, E.F., Meyfroidt, P., 2010. Land use transitions: Socio-ecological feedback versus socio-economic change. Land Use Policy 27, 108-118.

Lambin, E.F., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences 108, 3465-3472.

Laurent, C., van Rooyen, C.J., Madikizela, P., Bonnal, P., Carstens, J., 1999. Household typology for relating social diversity and technical change. Agrekon 38, 190-208.

LaValley, M.P., 2008. Logistic Regression. Circulation 117, 2395-2399.

Le, Q.B., 2005. Multi-agent system for simulation of land-use and land-cover change: a theoretical framework and its first implementation for an upland watershed in the Central Coast of Vietnam. Cuvillier Verlag, Göttingen.

Le, Q.B., Park, S.J., Vlek, P.L.G., Cremers, A.B., 2008. Land-Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–landscape system. I. Structure and theoretical specification. Ecological Informatics 3, 135-153.

Le, Q.B., Seidl, R., Scholz, R.W., 2012a. Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. Environmental Modelling & Software 27–28, 83-96.

Le, Q.B., Tamene, L., Vlek, P.L.G., 2012b. Multi-pronged assessment of land degradation in West Africa to assess the importance of atmospheric fertilization in masking the processes involved. Global and Planetary Change 92–93, 71-81.

Leisz, S.J., Thu Ha, N.t., Bich Yen, N.t., Lam, N.T., Vien, T.D., 2005. Developing a methodology for identifying, mapping and potentially monitoring the distribution of general farming system types in Vietnam's northern mountain region. Agricultural Systems 85, 340-363.

Lemke, U., Valle Zárate, A., 2008. Dynamics and developmental trends of smallholder pig production systems in North Vietnam. Agricultural Systems 96, 207-223.

Li, A., Wu, J., Huang, J., 2012. Distinguishing between human-induced and climate-driven vegetation changes: a critical application of RESTREND in inner Mongolia. Landscape Ecology, 1-14.

Linh, V.H., 2012. Efficiency of rice farming households in Vietnam. International Journal of Development Issues 11, 60-73.

Liu, J., Fritz, S., van Wesenbeeck, C.F.A., Fuchs, M., You, L., Obersteiner, M., Yang, H., 2008. A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Global and Planetary Change 64, 222-235.

Luckmann, J., Ihle, R., Grethe, H., Kleinwechter, U., 2011. Can Vietnamese Upland Farmers Profit from High World Market Prices? A Price Transmission Analysis. European Association of Agricultural Economists.

Lungu, O.I.M., Dynoodt, R.F.P., 2008. Acidification from long-term use of urea and its effect on selected soil properties. African Journal of Food Agriculture Nutrition and Development 8, 63-76.

Makokha, S., Kimani, S., Mwangi, W., Verkuijl, H., Musembi, F., 2001. Determinants of Fertilizer and Manure Use in Maize Production in Kiambu District, Kenya. D.F.: International Maize and Wheat Improvement Center (CIMMYT) and Kenya Agricultural Research Institute (KARI), Mexico.

Mambo, J., Archer, E., 2007. An assessment of land degradation in the Save catchment of Zimbabwe. Area 39, 380-391.

Marenya, P.P., Barrett, C.B., 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. Food Policy 32, 515-536.

Marenya, P.P., Barrett, C.B., 2009. Soil quality and fertilizer use rates among smallholder farmers in western Kenya. Agricultural Economics 40, 561-572.

Markon, C.J., Fleming, M.D., Binnian, E.F., 1995. Characteristics of vegetation phenology over the Alaskan landscape using AVHRR time-series data. Polar Record 31, 179-190.

Marquette, C.M., 1997. TTurning but not Toppling Malthus: Boserupian Theory on Population and the Environment Relationships. Chr. Michelsen Institute for Development Studies and Human Rights, Bergen, Norway.

Marten, G.G., 2001. Human ecology: basic concepts for sustainable development. Earthscan Publications, London, Sterling, VA.

Mbow, C., Fensholt, R., Rasmussen, K., Diop, D., 2013. Can vegetation productivity be derived from greenness in a semi-arid environment? Evidence from ground-based measurements. Journal of Arid Environments 97, 56-65.

MEA, 2005. Ecosystems and Human Well-being: Desertification Synthesis, Millennium Ecosystem Assessment. World Resources Institute, Washington, DC.

Metternicht, G., Zinck, J.A., Blanco, P.D., del Valle, H.F., 2010. Remote Sensing of Land Degradation: Experiences from Latin America and the Caribbean. J. Environ. Qual. 39, 42-61.

Meyfroidt, P., Lambin, E.F., 2009. Forest transition in Vietnam and displacement of deforestation abroad. Proceedings of the National Academy of Sciences 106, 16139-16144.

Miao, Y., Stewart, B., Zhang, F., 2011. Long-term experiments for sustainable nutrient management in China. A review. Agronomy Sust. Developm. 31, 397-414.

Michaud, J., Turner, S., Roche, Y., 2002. Mapping ethnic diversity in highland Northern Vietnam. GeoJournal 57, 305-323.

Middleton, N., Thomas, D., 1997. World Atlas of Desertification. UNEP, 182 p pp.

Minot, N., Baulch, B., 2005. Spatial patterns of poverty in Vietnam and their implications for policy. Food Policy 30, 461-475.

Minot, N., Baulch, B., Epperecht, M., 2006. Poverty and inequality in Vietnam: spatial patterns and geographic determinants. International Food Policy Research Institute (IFPRI).

Minot, N., Goletti, F., 2000. Rice Market Liberalization and Poverty in Vietnam. International Food Policy Research Institute, Washington, D.C.

Minot, N., Kherallah, M., Berry, P., 2000. Fertilizer market reform and the determinants of fertilizer use in Benin and Malawi. International Food Policy Research Institute (IFPRI).

Mitchell, T.D., Jones, P.D., 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. International Journal of Climatology 25, 693-712.

Miyasaka, T., Le, Q.B., Okuro, T., Zhao, X., Scholz, R.W., Takeuchi, K., 2012. An agent-based model for assessing effects of a Chinese PES programme on land-use change along with livelihood dynamics, and land degradation and restoration, in: Seppelt, R., Voinov, A.A., Lange, S., Bankamp, D. (Eds.), International Congress on Environmental Modelling and Software: Managing Resources of a Limited Planet. International Environmental Modelling and Software Society (iEMSs), Leipzig, Germany, pp. 2292-2299.

MoNRE, 2005. National Land Use Map. Ministry of Natural Resource and Environment, Vietnam.

Moran, P.A.P., 1950. Notes on Continuous Stochastic Phenomena. Biometrika 37, 17-23.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254-257.

Müller, D., Munroe, D.K., 2005. Tradeoffs between Rural Development Policies and Forest Protection: Spatially Explicit Modeling in the Central Highlands of Vietnam. Land Economics 81, 412-425.

Müller, D., Zeller, M., 2002. Land use dynamics in the central highlands of Vietnam: a spatial model combining village survey data with satellite imagery interpretation. Agricultural Economics 27, 333-354.

Munroe, D.K., Southworth, J., Tucker, C.M., 2002. The dynamics of land-cover change in western Honduras: exploring spatial and temporal complexity. Agricultural Economics 27, 355-369.

Mussgnug, F., Becker, M., Son, T.T., Buresh, R.J., Vlek, P.L.G., 2006. Yield gaps and nutrient balances in intensive, rice-based cropping systems on degraded soils in the Red River Delta of Vietnam. Field Crops Research 98, 127-140.

Mutert, E.W., 1996. Plant nutrient balances in the Asia and Pacific Region: Facts and consequences for agricultural production, in: Ahmed, S. (Ed.), Appropriate use of fertilizers in Asia and the Pacific. Food and Fertilizer Technology Center, Taipei.

Nachtergaele, F., Petri, M., 2008. Mapping land use systems at global and regional scales for land degradation assessment analysis. LADA. FAO, Rome.

NAP, 2002. Vietnam National Action Programme to Combat Desertification, Vietnam NAP for UNCCD Implementation, Hanoi, Vietnam.

NAP, 2006. National Action Programme to Combat Desertification for the Period 2006–2010 and orientation to 2020, National Action Programme of Viet Nam.

Nelson, G.C., Harris, V., Stone, S.W., 2001. Deforestation, Land Use, and Property Rights: Empirical Evidence from Darién, Panama. Land Economics 77, 187-205.

Nemecek, T., Dubois, D., Huguenin-Elie, O., Gaillard, G., 2011a. Life cycle assessment of Swiss farming systems: I. Integrated and organic farming. Agricultural Systems 104, 217-232.

Nemecek, T., Huguenin-Elie, O., Dubois, D., Gaillard, G., Schaller, B., Chervet, A., 2011b. Life cycle assessment of Swiss farming systems: II. Extensive and intensive production. Agricultural Systems 104, 233-245.

Nkonya, E., Gerber, N., Baumgartner, P., von Braun, J., De Pinto, A., Graw, V., Kato, E., Kloos, J., Walter, T., 2011a. The economics of land degradation: Toward an integrated global assessment. Peter Lang, Frankfurt am Mainz.

Nkonya, E., Schroeder, T., Norman, D., 1997. Factors affecting adoption of improved maize seed and fertiliser in Northern Tanzania. Journal of Agricultural Economics 48, 1-12.

Nkonya, E., Winslow, M., Reed, M.S., Mortimore, M., Mirzabaev, A., 2011b. Monitoring and assessing the influence of social, economic and policy factors on sustainable land management in drylands. Land Degradation & Development 22, 240-247.

Norton, D., Shainberg, I., Cihacek, L., Edwards, J.H., 1996. Erosion and Soil Chemical Properties, in: Lal, R. (Ed.), Soil Quality and Soil Erosion. Soil and Water Conservation Society, CRC Press, Boca, Raton, London, New York, Washington, D.C.

Olayide, O.E., Alene, A.D., Ikpi, A., 2009. Determinants of Fertilizer Use in Northern Nigeria. Pakistan Journal of Social Sciences 6, 91-98.

Oldeman, L.R., Hakkeling, R.T.A., Sombroek, W.G., 1991. World map of the status of human-induced soil degradation: an explanatory note, 2 ed. Wageningen: International Soil Reference and Information Centre; Nairobi: United Nations Environment Programme.

Omamo, S.W., Williams, J.C., Obare, G.A., Ndiwa, N.N., 2002. Soil fertility management on small farms in Africa: evidence from Nakuru District, Kenya. Food Policy 27, 159-170.

Omuto, C.T., Balint, Z., Alim, M.S., 2011. A framework for national assessment of land degradation in the drylands: A case study of Somalia. Land Degradation & Development, n/a-n/a.

Pandey, S., Khiem, N.T., Waibel, H., Thien, T.C., 2006. Upland rice household food security, and commercialization of upland agriculture in Vietnam. International Rice Research Institute, Los Baños, Laguna.

Pandey, S., van Minh, D., 1998. A socio-economic analysis of rice production systems in the uplands of northern Vietnam. Agriculture, Ecosystems & Environment 70, 249-258.

Park, S.J., Van de Giesen, N., Vlek, P.L.G., 2005. Optimal spatial scale for land use change modelling: A case study in a savanna landscape in Northern Ghana. Journal of the Korean Geographical Society 40, 221-241.

Paudel, P., Shrestha, A.K., Matsuoka, A., 2009. Socio-economic Factors Influencing Adoption of Fertilizer for Maize Production in Nepal: A Cast Study of Chitwan District, 83rd Annual Conference of the Agricultural Economics Society, Dublin, Ireland.

Pender, J., Nkonya, E., Jagger, P., Sserunkuuma, D., Ssali, H., 2006. Strategies to increase agricultural productivity and reduce land degradation in Uganda: an econometric analysis, in: Pender, J., Place, F., Ehui, S. (Eds.), Strategies for Sustainable Land Management in the East African Highlands. International Food Policy Research Institute, Washington, USA, pp. 165-189.

Pepe, M., Janes, H., Longton, G., Leisenring, W., Newcomb, P., 2004. Limitations of the odds ratio in gauging the performance of a diagnostic, prognostic, or screening marker. American Journal of Epidemiology 159, 882-890.

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.-M., Tucker, C.J., Stenseth, N.C., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology & Evolution 20, 503-510.

Phien, T., Siem, N.T., 1998. Sustainable cultivation on sloping land in Viet Nam. Agricutural Publising House, Hanoi.

Pickup, G., Chewings, V.H., 1994. A grazing gradient approach to land degradation assessment in arid areas from remotely-sensed data. International Journal of Remote Sensing 15, 597 - 617.

Pinter, P.J., Jackson, R.D., Elaine Ezra, C., Gausman, H.W., 1985. Sun-angle and canopy-architecture effects on the spectral reflectance of six wheat cultivars. International Journal of Remote Sensing 6, 1813-1825.

Pinzon, J., Brown, M.E., Tucker, C.J., 2005. Satellite time series correction of orbital drift artifacts using empirical mode decomposition. In: N. Huang (Editor), Hilbert–Huang Transform: Introduction and Applications, pp 167-186.

Quang, D.V., 2010. Innovations and Sustainability Strategies in the Upland Agriculture of Northern Vietnam: An Agent-Based Modeling Approach. Economy and Environment Program for Southeast Asia (EEPSEA).

Quang, D.V., Schreinemachers, P., Berger, T., 2014. Ex-ante assessment of soil conservation methods in the uplands of Vietnam: An agent-based modeling approach. Agricultural Systems 123, 108-119.

Quy, D.V., Hirose, K., Mauyama, Y., Yamashita, M., Hang, H.T.N., 2001. Using Satellite Data and Geo-Environmental Research for Environmental Monitoring of Bau Trang Lake area, Bin Thuan Province, Vietnam. Paper presented at the 22nd Asian Conference on Remote Sensing, 5–9 November 2001, Singapore.

Rakhlin, A., Caponnetto, A., 2006. Stability of K-means Clustering, Neural Information Processing Systems Conference, Vancouver, B.C., Canada.

Reddy, V.R., 2003. Land degradation in India: extent, costs and determinants. Economic and Political Weekly 38, 4700-4713.

Reed, M.S., Buenemann, M., Atlhopheng, J., Akhtar-Schuster, M., Bachmann, F., Bastin, G., Bigas, H., Chanda, R., Dougill, A.J., Essahli, W., Evely, A.C., Fleskens, L., Geeson, N., Glass, J.H., Hessel, R., Holden, J., Ioris, A.A.R., Kruger, B., Liniger, H.P., Mphinyane, W., Nainggolan, D., Perkins, J., Raymond, C.M., Ritsema, C.J., Schwilch, G., Sebego, R., Seely, M., Stringer, L.C., Thomas, R., Twomlow, S., Verzandvoort, S., 2011. Cross-scale monitoring and assessment of land degradation and sustainable land management: A methodological framework for knowledge management. Land Degradation & Development 22, 261-271.

Reynolds, J.F., Grainger, A., Stafford Smith, D.M., Bastin, G., Garcia-Barrios, L., Fernández, R.J., Janssen, M.A., Jürgens, N., Scholes, R.J., Veldkamp, A., Verstraete, M.M., Von Maltitz, G., Zdruli, P., 2011. Scientific concepts for an integrated analysis of desertification. Land Degradation & Development 22, 166-183.

Reynolds, J.F., Smith, D.M.S., Lambin, E.F., Turner II, B.L., Mortimore, M., Batterbury, S.P.J., Downing, T.E., Dowlatabadi, H., Fernandez, R.J., Herrick, J.E., Huber-Sannwald, E., Jiang, H., Leemans, R., Lynam, T., Maestre, F.T., Ayarza, M., Walker, B., 2007. Global desertification: building a science for dryland development. Science 316, 847-851. http://www.ncbi.nlm.nih.gov/pubmed/17495163.

Robinson, F., Apon, A., Brewer, D., Dowdy, L., Hoffman, D., Lu, B., 2006. Initial Starting Point Analysis for K-Means Clustering: A Case Study, Proceedings of ALAR 2006 Conference on Applied Research in Information Technology, Conway, Arkansas, USA.

Roy, R.N., Misra, R.V., Lesschen, J.P., E.M.Smaling, 2003. Assessment Of Soil Nutrient Balance: Approaches And Methodologies. Food and Agriculture Organization of The United Nation, Rome.

Rudel, T., 1989. Population, development, and deforestation: A cross-national analysis. Rural Sociology 57, 327-338.

Rudel, T., Roper, J., 1997. The paths to rain forest destruction: Crossnational patterns of tropical deforestation, 1975–1990. World Development 25, 53-65.

Safriel, U.N., 2007. The assessment of global trends in land degradation, in: Sivakumar, M.V.K., Ndiang'ui, N. (Eds.), Climate and Land Degradation. Springer Verlag, Berlin, pp. 1-38.

Scherr, S., Hazell, P., 1994. Sustainable agricultural development strategies in fragile lands. Environment and Production Technology Division, International Food Policy Research Institute, Washington DC, USA.

Scherr, S., Jackson, L.A., Templeton, S., 1995. "Living on the edge: Crafting land use policies for the tropical hillsides in 2020". Paper presented at the workshop on Land Degradation in the Developing World: Implications for Food, Agriculture and the Environment to the year 2020. International Food Policy Research Institute. Annapolis MD USA April 4-6.

Scherr, S.J., 2000. A downward spiral? Research evidence on the relationship between poverty and natural resource degradation. Food Policy 25, 479-498.

Scherr, S.J., Yadav, S.N., 1996. Land degradation in the developing world: implications for food, agriculture, and the environment to 2020. International Food Policy Research Institute (IFPRI).

Scholz, R.W., Tietje, O., 2002. Embedded Case Study Methods: Integrating Quantitative and Qualitative Knowledge. Sage Publications, Thousand Oaks, California.

SDS, 2009. Son La Statistical Year Book. Statistic Department of Son La, Son La, Vietnam.

Shepherd, K.D., Walsh, M.G., 2002. Development of reflectance spectral libraries for characterization of soil properties. Soil Science Society of America Journal 66, 988–998.

Shrestha, D.P., Margate, D.E., Meer, F.v.d., Anh, H.V., 2005. Analysis and classification of hyperspectral data for mapping land degradation: An application in southern Spain. International Journal of Applied Earth Observation and Geoinformation 7, 85-96.

Sidle, R.C., Ziegler, A.D., Negishi, J.N., Nik, A.R., Siew, R., Turkelboom, F., 2006. Erosion processes in steep terrain—Truths, myths, and uncertainties related to forest management in Southeast Asia. Forest Ecology and Management 224, 199-225.

Siem, N.T., Phien, T., 1999. Upland Soils in Vietnam - Degradation and Rehabilitation. Agricultural Publishing House. Hanoi.

Smajgl, A., Bohensky, E., 2013. Behaviour and space in agent-based modelling: Poverty patterns in East Kalimantan, Indonesia. Environmental Modelling & Software 45, 8-14.

Sommer, S., Zucca, C., Grainger, A., Cherlet, M., Zougmore, R., Sokona, Y., Hill, J., Della Peruta, R., Roehrig, J., Wang, G., 2011. Application of indicator systems for monitoring and assessment of desertification from national to global scales. Land Degradation & Development 22, 184-197.

Sonneveld, B.G.J.S., 2003. Formalizing expert judgements in land degradation assessment: a case study for Ethiopia. Land Degradation & Development 14, 347-361.

Stibig, H.-J., Upik, R., Beuchle, R., Hildanus, Mubareka., S., 2000. The Land Cover Map for South East Asia in the Year 2000. GLC2000 database, European Commision Joint Research Centre, 2003. http://www-gem.jrc.it/glc2000.

Stocking, M., Murnaghan, N., 2001. Handbook for the field assessment of land degradation. Earthscan Publications, London (UK).

Stolbovoi, V., Fischer, G., 1997. A New Digital Georeferenced Database of Soil Degradation in Russia. International Institute for Applied Systems Analysis, Interim report IR-97-084/November.

Stringer, L.C., 2012. Global land and soil degradation: challenges to soil - An issue paper, Global Soil Week 2012. Global Soil Forum, Institute for Advanced Sustainability Studies Postdam.

Symeonakis, E., Drake, N., 2004. Monitoring desertification and land degradation over sub-Saharan Africa. International Journal of Remote Sensing 25, 573 - 592.

Thanh, N.C., Singh, B., 2006. Trend in rice production and export in Vietnam. Omonrice Journal 14, 111-123.

Thao, L.B., 2001. Vietnam – Territory and Geographic Regions. World Publisher, Ha Noi, Vietnam.

Thiam, A.K., 2003. The causes and spatial pattern of land degradation risk in southern Mauritania using multitemporal AVHRR-NDVI imagery and field data. Land Degradation & Development 14, 133-142.

Thomas, W., 1997. A three-dimensional model for calculating reflection functions of inhomogeneous and orographically structured natural landscapes. Remote Sensing of Environment 59, 44-63.

Thuy, N.T.T., Wu, M.-H., Lai, T.V., 2002. Northern Vietnam, in: Ali, M. (Ed.), The Vegetable Sector in Indochina Countries: Farm and Household Perspectives on Poverty Alleviation. Asian Regional Center (ARC, Thailand) and Asian Vegetable Research and Development Center (AVRDC, Taiwan), Taiwan, pp. 113-153.

Tiffen, M., Mortimore, M., Gichuki, F., 1994. More People – Less Erosion: Environmental Recovery in Kenya. Wiley and Sons, London, UK.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences 108, 20260-20264.

Tittonell, P., Muriuki, A., Shepherd, K.D., Mugendi, D., Kaizzi, K.C., Okeyo, J., Verchot, L., Coe, R., Vanlauwe, B., 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa – A typology of smallholder farms. Agricultural Systems 103, 83-97.

Tran, T.M., Bui, H.H., Luxhøi, J., Jensen, L.S., 2012. Application rate and composting method affect the immediate and residual manure fertilizer value in a maize–rice–rice–maize cropping sequence on a degraded soil in northern Vietnam. Soil Science and Plant Nutrition 58, 206-223.

Tuan, V.D., Hilger, T., MacDonald, L., Clemens, G., Shiraishi, E., Vien, T.D., Stahr, K., Cadisch, G., 2014. Mitigation potential of soil conservation in maize cropping on steep slopes. Field Crops Research 156, 91-102.

Tucker, C.J., Pinzon, J.E., Brown, M.E., Slayback, D.A., Pak, E.W., Mahoney, R., Vermote, E.F., El Saleous, N., 2005. An extended AVHRR 8km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. International Journal of Remote Sensing 26, 4485-4498.

Tuomisto, H.L., Hodge, I.D., Riordan, P., Macdonald, D.W., 2012. Comparing energy balances, greenhouse gas balances and biodiversity impacts of contrasting farming systems with alternative land uses. Agricultural Systems 108, 42-49.

UNCCD, 2004. Preserving our common ground - UNCCD 10 years on. Secretariat of the United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.

UNCCD, 2006. Vietnam National Report on The UNCCD Implementation 2006, Ha Noi, p. 32.

USGS, 2004. Shuttle Radar Topography Mission, 1 Arc Second scene SRTM_u03_n008e004, Unfilled Unfinished 2.0, Global Land Cover Facility, University of Maryland, College Park, Maryland, February 2000. .

van Lynden, G.W.J., 2000. Soil degradation in Central and Eastern Europe. The assessment of the status of human-induced soil degradation, FAO and ISRIC, Report 2000/5. 15 p.

van Lynden, G.W.J., Oldeman, L.R., 1997. Assessment of the Status of Human-induced soil degradation in South and South East Asia. International Soil Reference and Information Centre, Wageningen. 35 p. http://lime.isric.nl/Docs/ASSODEndReport.pdf.

Vanlauwe, B., Bationo, A., Chianu, J., Giller, K.E., Merckx, R., Mokwunye, U., Ohiokpehai, O., Pypers, P., Tabo, R., Shepherd, K.D., Smaling, E.M.A., Woomer, P.L., Sanginga, N., 2010. Integrated soil fertility management: Operational definition and consequences for implementation and dissemination. Outlook on Agriculture 39, 17-24.

Veldkamp, A., Verburg, P.H., Kok, K., de Koning, G.H.J., Priess, J., Bergsm, A.R., 2001. The need for scale sensitive approaches in spatially explicit land use change modeling. Environmental Modeling and Assessment 6, 111-121.

Verburg, P.H., de Nijs, T.C.M., Ritsema van Eck, J., Visser, H., de Jong, K., 2004. A method to analyse neighbourhood characteristics of land use patterns. Computers, Environment and Urban Systems 28, 667-690.

Vezina, K., Bonn, F., Van, C., 2006. Agricultural land-use patterns and soil erosion vulnerability of watershed units in Vietnam's northern highlands. Landscape Ecology 21, 1311-1325.

Vien, T.D., 2003. Culture, environment, and farming systems in Vietnam's northern mountain region. Southeast Asian Studies 41, 180-205.

Vlek, P.L.G., Le, Q.B., Tamene, L., 2008. Land Decline in Land-Rich Africa: A Creeping Disaster in the Making. CGIAR Science Council Secretariat, Rome, Italy.

Vlek, P.L.G., Le, Q.B., Tamene, L., 2010. Assessment of land degradation, its possible causes and threat to food security in sub-Saharan Africa, in: Lal, R.a.S., B.A. (Ed.), Food Security and Soil Quality. Taylor and Francis, p. 430.

Vogt, J.V., Safriel, U., Von Maltitz, G., Sokona, Y., Zougmore, R., Bastin, G., Hill, J., 2011. Monitoring and assessment of land degradation and desertification: Towards new conceptual and integrated approaches. Land Degradation & Development 22, 150-165.

Von Braun, J., Gerber, N., 2012. The Economics of Land and Soil Degradation-Toward an Assessment of the Costs of Inaction, in: Lal, R., Lorenz, K., Hüttl, R.F., Schneider, B.U., von Braun, J. (Eds.), Recarbonization of the Biosphere. Springer Netherlands, pp. 493-516.

Von Braun, J., Gerber, N., Mirzabaev, A., Nkonya, E., 2012. The economic of land degradation - An issue paper, Global Soil Week 2012. Global Soil Forum, Institute for Advanced Sustainability Studies Postdam, pp. 1-30.

Vu, M.Q., Le, Q.B., Frossard, E., Vlek, P.L.G., 2014a. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level. Land Use Policy 36, 605-617.

Vu, Q.M., Le, Q.B., Vlek, P.L.G., 2014b. Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation. Global and Planetary Change 121, 64-77.

Vu, M.Q., Le, Q.B., Scholz, R.W., Vlek, P.L.G., 2012a. Detecting geographic hotspots of human-induced land degradation in Vietnam and characterization of their social–ecological types, Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pp. 6220-6223.

Vu, Q.D., Tran, T., Nguyen, P., Vu, C., Vu, V., Jensen, L., 2012b. Effect of biogas technology on nutrient flows for small- and medium-scale pig farms in Vietnam. Nutrient Cycling in Agroecosystems 94, 1-13.

Vu, T.K.V., Tran, M.T., Dang, T.T.S., 2007. A survey of manure management on pig farms in Northern Vietnam. Livestock Science 112, 288-297.

Waithaka, M., Thornton, P., Shepherd, K., Ndiwa, N., 2007. Factors affecting the use of fertilizers and manure by smallholders: the case of Vihiga, western Kenya. Nutrient Cycling in Agroecosystems 78, 211-224.

WCED, 1987. Our Common Future. World Commission on Environment and Development, Oxford: Oxford University Press.

Wessels, K.J., 2009. Letter to the Editor - Comments on 'Proxy global assessment of land degradation' by Bai et al. (2008). Soil Use and Management 25, 91-92.

Wessels, K.J., Prince, S.D., Frost, P.E., van Zyl, D., 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sensing of Environment 91, 47-67.

Wessels, K.J., Prince, S.D., Malherbe, J., Small, J., Frost, P.E., VanZyl, D., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. Journal of Arid Environments 68, 271-297.

Wezel, A., Luibrand, A., Thanh, L.Q., 2002a. Temporal changes of resource use, soil fertility and economic situation in upland Northwest Vietnam. Land Degradation & Development 13, 33-44.

Wezel, A., Steinmüller, N., Friederichsen, J.R., 2002b. Slope position effects on soil fertility and crop productivity and implications for soil conservation in upland northwest Vietnam. Agriculture, Ecosystems & Environment 91, 113-126.

Williams, A., Audsley, E., Sandars, D., 2010. Environmental burdens of producing bread wheat, oilseed rape and potatoes in England and Wales using simulation and system modelling. Int J Life Cycle Assess 15, 855-868.

Wischmeier, W.C., 1976. Use and misuse of the Universal Soil Loss Equation. Journal of Soil and Water Conservation 31, 5-9.

Wu, Z., Huang, N.E., Long, S.R., Peng, C.-K., 2007. On the trend, detrending, and variability of nonlinear and nonstationary time series. Proceedings of the National Academy of Sciences 104, 14889-14894.

Xiao, Z., Liang, S., Wang, J., Chen, P., Yin, X., Zhang, L., Song, J., 2013. Use of general regression neural networks for generating the GLASS Leaf Area Index product from time-series MODIS surface reflectance. IEEE Transactions on Geoscience and Remote Sensing 99, 1-15.

Zhang, F.S., Fan, M.S., Zhao, B.Q., Chen, X.P., Li, L., Shen, J.B., Feng, G., Chen, Q., Jiang, R.F., Ma, W.Q., Zhang, W.F., Cui, Z.L., Fan, X.L., 2006. Fertilizer use, soil fertility and integrated nutrient management in China, in: Fan, M.S., Zhang, F.S. (Eds.), Improving Plant Nutrient Management for Better Farmer Livelihoods, Food Security and Environmental Sustainability. FAO, pp. 188-211.

Zhao, M., Running, S.W., 2010. Drought-induced reduction in global terrestrial Net Primary Production from 2000 through 2009. Science 329, 940-943.

Zhao, M., Running, S.W., 2011. Response to comments on “Drought-induced reduction in global terrestrial Net Primary Production from 2000 through 2009”. Science 333, 1093.

Zhou, Y., Yang, H., Mosler, H.-J., Abbaspour, K.C., 2010. Factors Affecting Farmers Decisions on Fertilizer Use: A Case Study for the Chaobai Watershed in Northern China. Consilience: The Journal of Sustainable Development 4, 80-102.

# Publications

## Peer-reviewed publications

**Vu, Q.M.**, Le, Q.B., Vlek, P.L.G., 2014. Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation. *Global and Planetary Change* 121, 64-77. DOI: 10.1016/j.gloplacha.2014.07.007

**Vu, Q.M**, Le, Q.B., Frossard, E., Vlek, P.L.G., 2014. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level. *Land Use Policy* 36, 605 - 617. DOI: 10.1016/j.landusepol.2013.10.012

## Conference proceedings (peer-reviewed)

**Vu, M.Q.**, Le, Q.B., Scholz, R.W., Vlek, P.L.G. 2012. Detecting geographic hotspots of human-induced land degradation in Vietnam and characterization of their social–ecological types. *Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International*: 6220-6223. DOI: 10.1109/IGARSS.2012.6352679

## Manuscripts in Preparation

**Vu, Q.M.**, Frossard, E.,Vlek, P.L.G., Krütli, P., Stauffacher, M., Le, Q.B. (in prep). The importance of livelihood diversity in determining households' decisions on fertilizer use. Land Use Policy