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Development of integrated modeling framework of land use changes and ecosystem services in mountainous watersheds

Dissertation

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Summary

Land use and cover changes (LUCC) are complex phenomena- causing changes on ecosystem services (ES). The importance of LUCC and ES have widely been recognized by the human society and thus ES are increasingly considered in policy making. Land management policies should achieve policy objectives whilst minimizing side effects and to develop better management plans sustainably. Therefore, integrated modeling frameworks of LUCC and ES are useful policy support tools for sustainable management.

This dissertation suggests an integrated modeling framework, which simulates spatial LUCC and the response of water-related ES in a mountainous watershed. The specific objectives are: (1) to quantify LUCC patterns and their natural-environment al and socio-economic driving factors; (2) to simulate LUCC and ES under different policy options through an integrated modeling framework of cellular automata (CA) and hydrological modeling; and (3) to simulate agricultural LUCC and ES via an agent-based model (ABM) reflecting farmers' decision-making processes in one hotspot sub-region.

In the first chapter, patterns and factors of LUCC was analyzed in archetypical periods of LUCC in Soyang Watershed in South Korea. Dominant patterns of LUCC were urban and agricultural expansion from 1980-90; in contrast, reforestation was advanced in 1990-2000. LUCC was mainly affected by slope and neighboring land composition for all types while agricultural land was more affected by rainfall and deregulation. Urban expansion was affected by land development plans, including dam and highway constructions. Agricultural areas were also affected by regional climate changes by dam construction and changes in crop price. Forest expansions occurred in areas with lower accessibility which worsen agricultural conditions, reflecting natural conversions of abandoned farms.

In the second chapter, an integrated modeling framework was developed using CA and the hydrological model SWAT (Soil and Water Assessment Tool) for different policy scenarios. There were similar patterns of reforestation in marginal agricultural areas regardless of policy types while the magnitude of reforestation

was affected by the policy. Forest areas increase by 0.8% and dry fields decrease by 5% in the baseline scenario, while forest increase by 2.5% and dry fields decrease by 43% in the mixed policy of forest protection and reforestation. When these results are used to estimate water related ES, there was a decrease by up to 8% in sediment, the baseline scenario decreases sediment by 8%, total nitrogen (N) by 3%, and total phosphorus (P) by 1% while the combined policy decreases sediment by 48%, total N by 21%, and total P by 30%.

In the third chapter, ABM was adopted to develop an integrated model for one sub-region considered as water pollution "hotspot", which simulated agricultural land use and the resulting soil erosion. Farmers with large sized farms converted less of their land to perennial crops, whilst maintaining current field status (rice and annual crops), resulting in a moderate decrease in soil erosion. Fallow lands could expand by up to 7%, increasing soil erosion rate by 6%. In two different fallow land management scenarios (ginseng farm and perennial crop expansions), the ginseng expansion plan is more effective at reducing soil erosion than perennial crop expansions.

In this dissertation, integrated modeling frameworks are developed using various models (CA, ABM, SWAT, and RUSLE) to estimate the spatial distribution of LUCC impacts on water quality-related ES under different land management policies. Based on the simulation results, agriculture and forest areas played an important role in improving or worsening water quality in the watershed area and thus should be controlled by appropriate management plans. Although these models still show a number of limitations, they could expand their spatial scale and help to update individual decision-making and interactions of all stakeholders.

Zusammenfassung

Landnutzungswandel ist ein komplexes Phänomen, das Veränderungen von Ökosystemleistungen nach sich zieht. Die Bedeutung von Landnutzungswandel und Ökosystemleistungen wurde in der Gesellschaft weithin anerkannt, wodurch Ökosystemleistungen in zunehmendem Maße Berücksichtigung in politischen Entscheidungen gefunden haben. Landnutzungspolitik sollte demnach die politischen Zielvorgaben erfüllen und gleichzeitig Nebeneffekte minimieren sowie nachhaltige Managementstrategien entwickeln. Aus diesem Grund sind integrierte Modellierungssysteme, die sowohl Landnutzungsveränderungen als auch Ökosystemleistungen einbeziehen, nützliche Entscheidungshilfen für nachhaltiges Management.

Diese Dissertation stellt ein integriertes Modellsystem vor, welches räumlich explizit Landnutzungsveränderungen und deren Folgen auf wasserqualitätsbezogene Ökosystemleistungen in einem gebirgigen Einzugsgebiet simuliert. Die Zielstellungen dieser Arbeit sind (1) die Quantifizierung von Landnutzungsmustern und deren naturräumlichen und sozio-ökonomischen Einflussfaktoren, (2) die Simulation von Landnutzungswandel und Ökosystemleistungen unter dem Einfluss verschiedener Politikinstrumente mithilfe eines integrierten Systems aus Cellular Automata (CA) und hydrologischer Modellierung und (3) die Simulation landwirtschaftlicher Nutzungsveränderungen und Ökosystemleistungen mithilfe eines Agenten-basierten Modells (ABM), welches die Entscheidungsprozesse von Landwirten abbildet.

Für die erste Fragestellung wurden die räumlichen Muster des Landnutzungswandels in der Untersuchungsregion des Soyang-Einzugsgebietes untersucht, welche zwischen 1980 und 90 durch die Ausweitung urbaner und landwirtschaftlicher Flächen dominiert war, während zwischen 1990 und 2000 eine Wiederaufforstung zu verzeichnen war. Die Landnutzungsveränderungen wurden in erster Linie durch die Hangneigung und die Zusammensetzung benachbarter Landnutzungseinheiten bestimmt, während landwirtschaftliche Flächen stärker durch Niederschlag und Deregulierung beeinflusst wurden. Die städtische Ausdehnung wurde durch Landentwicklungsplanungen, wie die Konstruktion von Staudämmen und Fernstraßen beeinflusst. Landwirtschaftliche Flächen wurden durch den regionalen Klimawandel, der im Zusammenhang mit Staudammkonstruktionen steht, und die veränderungen der Erntepreise. Die

Ausdehnung der Waldflächen fand in Gebieten mit geringer Zugänglichkeit statt, welches die landwirtschaftlichen Produktionsbedingen erschwerte, und war stärker ausgeprägt in der Nähe von bestehenden Waldflächen und reflektiert somit die natürliche Umwandlung von stellgelegtem Agrarland.

Im zweiten Teil wurde ein Modellsystem aus CA und dem hydrologischen Modell SWAT (Soil and Water Assessment Tool) für unterschiedliche Politikszenarien entwickelt. Unabhängig von der Art der Politikinstrumente wurden ähnliche (räumliche) Muster von Wiederaufforstung auf marginalen landwirtschaftlichen Flächen gefunden, während allerdings das Ausmaß der Wiederbewaldung durch die Politik beeinflusst war. Für das Baseline-Szenario erhöhen sich die Waldflächen um 0.8% und verringern sich trockene (nichtbewässerte) Anbauflächen um 5%, während sich bei einer kombinierten Schutz- und Aufforstungspolitik die Waldfläche um 2.5% erhöhen und die Anbauflächen um 43% zurückgehen. Wenn diese Ergebnisse in wasserqualitätsbezogene Ökosystemleistungen übertragen werden, verringern sich für das Baseline-Szenario Sediment um 8%, Gesamt-Stickstoff (N) um 3% und Gesamt-Phosphor (P) um 1%, während die kombinierte Politik einen Rückgang von Sediment um 48%, Gesamt-N um 21% und Gesamt-P um 30% zur Folge hat.

Im dritten Teil wurde ein ABM verwendet, um ein integriertes Modell für eine Teilregion zu entwickeln, die als „Hotspot" für Wasserverschmutzung gilt, um die landwirtschaftliche Nutzung und die daraus resultierende Bodenerosion zu simulieren. Landwirte mit großen Schlägen wandelten weniger Fläche ihres Landes in mehrjährige Kulturen um und behielten den gegenwärtigen Status (Reis und einjährige Feldfrüchte) bei, wodurch eine moderate Reduzierung der Bodenerosion erreicht wurde. Brachflächen konnten sich um bis zu 7% erhöhen, was die Bodenerosionsrate um 6% steigerte. In zwei verschiedenen Brachlandmanagementszenarien (Erweiterung des Ginseng-Anbaus und mehrjähriger Kulturen), zeigte sich, dass Ginseng-Anbau die Bodenerosion effektiver reduziert als die Ausweitung von mehrjährigen Kulturen.

In dieser Dissertation wurden integrierte Modellsysteme aus verschiedenen Modellen (CA, ABM, SWAT und RUSLE) entwickelt, um die räumliche Verteilung von Landnutzungsveränderungen und deren Auswirkungen auf wasserqualitätsbezogene Ökosystemleistungen für verschiedene Landnutzungspolitikmaßnahmen zu untersuchen. Anhand der Modellergebnisse kann geschlussfolgert werden, dass Landwirtschafts- und Waldflächen eine entscheidende Rolle in der Verbesserung bzw. Verschlechterung der Gewässerqualität im Einzugsgebiet spielen und deshalb durch angemessene

Maßnahmenplanungen reguliert werden sollten. Obwohl diese Modelle einige Beschränkungen aufweisen, können sie auf größere Skalen ausgeweitet werden und helfen, individuelle Entscheidungsprozesse und Interaktionen zwischen allen Stakeholdern zu verbessern.

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List of abbreviations

LUCC	Land use and cover changes
ES	Ecosystem services
CA	Cellular Automata
ABM	Agent-Based Model
SWAT	Soil and Water Assessment Tool
RUSLE	Revised Universal Soil Loss Equation
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
ARIES	Artificial Intelligence for Ecosystem Services
PES	Payment for Ecosystem Service
MNL	Multinomial logistic regression
LC	Land cover
EF	Enrichment factor
BC	Bounded confidence
VBSA	Variance-based sensitivity analysis
SUFI-2	Sequential Uncertainty Fitting
N	Nitrogen
P	Phosphorus
R	Rainfall / climate
K	Erosion
LS	Slope-length and slope
C	Vegetation / cover-management
P	Support-practice / practice
NO	current management scenario
R+P	Reforestation and protection
LSI	Land suitability index
GIS	Geographic information system
ROC	Relative operating characteristics

AUC	Area under the ROC curve
IDW	Inverted distance weight
REF	Reforestation program through direct payment to farmers
PRO	Protection program for high-slope areas
R+P	combined policy of reforestation and protection
NO	No intervention
HRU	Hydrologic response unit
BL	Baseline
MJ	Megajoule
USLE	Universal Soil Loss Equation
SCS	Soil conservation service
SWAT-CUP	SWAT Calibration and Uncertainty Procedures
NSE	Nash-Sutcliffe efficiency
PPU	Percent prediction uncertainty
P-factor (SWAT)	Percentage of observed data bracketed by the 95 PPU
R-factor (SWAT)	Average thickness of the 95 PPU
CBP	Capacity building program
BAU	Business as usual
S1	Fallow land growth
S2	perennial crop growth
S3	ginseng farm growth
MCE	Multi-criteria evaluation
S-MF	S-shaped membership function
K-MF	Kendal membership function
S	First-order sensitivity index
ST	Total effect sensitivity index

Chapter 1 Synopsis

1.1 Background and Motivation

1.1.1 Land use and cover change and ecosystem services in mountainous watershed

Land use and cover changes (LUCC) are complex phenomena resulting from interactions between human activities and natural ecosystems at specific temporal and spatial scales (Rindfuss et al., 2004). Human activities affect land through management practices to accomplish certain objectives of human society, which change the biophysical status of land and are significant driving factors of environmental changes from global climate changes to regional functions of ecosystems related to human vulnerability (Lambin et al., 2001; Foley et al., 2005; Turner et al., 2007). These changes of environmental functions lead to changes in ecosystem services (ES), which are necessary to sustain human well-being (Daily, 1997). ES are defined as direct or indirect human benefits from ecosystem functions, which are classified as provisioning (food, raw materials, fresh water and medicinal resources), regulating (local climate and air quality, carbon sequestration and storage, moderation of extreme events, waste-water treatment, erosion prevention and maintenance of soil fertility, pollination and biological control), cultural (recreation, mental and physical health, tourism, aesthetic appreciation and inspiration for culture, art and design, spiritual experience and sense of place) and habitat or supporting (habitats for species and maintenance of genetic diversity) services from natural environments (TEEB, 2010). These ES are fundamentally important to maintaining human societies (MA, 2005; TEEB, 2010) and thus ES for human benefit should accompany an understanding of the targeted ecosystem (Brauman et al., 2007). Moreover, ES are not affected by specific ecosystem boundaries and their impacts also vary depending on the spatial and temporal characteristics of the regional environment (Fisher et al., 2009).

In particular, mountainous areas are spatially heterogeneous ecosystems due to the characteristics of LUCC and these areas have a higher capacity of ES than others (Grêt-Ragamey et al., 2012). Mountainous watersheds in upstream catchment provide various ES to the downstream areas such as a provision of fresh water, erosion regulation and regulation of water quality and quantity (MA, 2005; TEEB, 2010). However, LUCC activities under land management plans (agriculture, forestation and urbanization) could alter the capacity of mountainous watersheds to deliver ES (Kremen, 2005; Vitousek et al., 1997). Especially, agricultural practices provide various resources (food, timber, and other goods) and also regulate ecosystem functions to human society (MA, 2005; Power, 2010), However, agricultural practices in upland watershed can alter ES capacity to regulate hydrological cycles and to provide fresh water to downstream areas due to growth in nutrients and sediment loads as a consequence of high fertilizer use and soil management in agricultural areas (Bennett et al., 2009; Bhaduri et al., 2000; Baker and Miller, 2013; Foley et al., 2005; Hascic and Wu, 2006; Montgomery, 2007). These impacts of agricultural activities also vary with types of agricultural systems beyond provisioning ES delivered by crops such as importance in perennial crops, which could regulate water quality and quantity (Power, 2010). Moreover, land abandonment in marginal farmlands decreases regulating ES due to severe soil erosion because abandoned areas have coarse vegetation covers than cultivated areas (Kosmos et al., 2000; Jain et al., 2001). Therefore, changes on ES resulting from LUCC should be considered in agricultural decision-making processes.

The importance of ES has widely been recognized by human society and thus ES are increasingly considered in policy making (Braat and de Groot, 2012; Daily and Matson, 2008; Kremen, 2005). However, ES management policies should consider the trade-off between different ES (Heal et al., 2001; Pereira et al., 2005; Rodriguez et al., 2006). Trade-offs between ES arise when human interventions to increase one ES cause declines in another ES as a result of LUCC as mentioned above (Körner, 2000; Schröter et al., 2005; Rounsevell et al., 2006; Polasky et al., 2011). Understanding those trade-offs, including assessment and identification of drivers among ES, is a major consideration in management plans (Bennett et al., 2009). In mountain ecosystems, provision of ES such as fresh water provision and regulating water quality is strongly affected by LUCC and spatial characteristics in regional ecosystems (Power, 2010). Management in mountain watershed, therefore, should be preceded with a consideration of LUCC such as agriculture for better management plans (Viviroli et al., 2003). However, the magnitude of land use effects on ES is still difficult to estimate due to lack of sufficient indicators of ES (Balmford et al., 2002; MA, 2005; Nelson et al., 2009). Under such circumstances, estimating ES should be considered in land-use decision-making processes, which focus management to strengthen regional specific ES (Goldstein et al., 2012; Nelson et al., 2009; Tallis and Polasky, 2009).

1.1.2 Estimating impacts of land management plans on land use and ecosystem services

Land management is a human activity to utilize natural resources for human societies, which influence regional LUCC (Kremen et al., 2007; Verburg and Overrmas, 2009). In particular, land management practices based on environmental and LU policies set the direction of land resource utilization and thus cause changes in regional LUCC and ES (Fisher et al., 2009; Carpenter et al., 2009; von Haaren and Albert, 2011; van Oudenhoven et al., 2012). Therefore, land management of stakeholders should be considered to understand ES (Heal, 2000; NRC, 2005; Daily et al., 2009). Land management plans and policies affect regional environmental systems where these plans are applied and thus cause changes of provisioning of ES (Chan et al., 2006; Naidoo and Ricketts, 2006; Fisher et al., 2009). However, human management plans such as LUCC can cause uncertain and unexpected responses of natural ecosystems intentionally and unintentionally due to complex and emergent characteristics of interactions between social and environmental systems, which cause trade-offs between ES (Fürst et al., 2013; Mohamed et al., 2000). Moreover, these trade-offs commonly occur at multiple scales and thus they may cause a dilemma in policy making, and even policy failure (Rodríguez et al., 2005; Taylor et al., 2012). To solve these problems, regional management plans for a specific policy purpose (e.g. regional development or conservation) should be based on an understanding of regional systems, which reflects interactions between human and natural systems to reduce trade-off among ES and optimize regional land management (Fürst et al., 2013).

Balance among ES is needed to achieve policy objectives whilst minimizing side effects arising from interactions within regional systems and to develop better management plans sustainably, which leads to both economic and environmental benefits (Lambin et al., 2001). However, benefits from ES outside the relevant political boundaries are often overlooked in the policy making process because these ES are less considered in current policy (Fürst et al., 2013). Therefore, integrated approaches are needed to support regional land management plans, which apply integrated concepts of LUCC and ES in regional systems and assess regional ES (de Groot et al., 2010; Fürst et al., 2013; Koschke et al., 2012; Pinto-Correira et al., 2006; Vejre et al., 2007). The development of policy support tools has several steps, such as establishment of indicators to assess ES provision, complexity of LUCC and ES, making a quantitative model of ES reflecting interactions with other ES, and spatial and temporal dimensions of ES (Turner and Daily, 2008; Carpenter et al., 2009; van Strien et al., 2009; Villa et al., 2009; de Groot et al., 2010, Bastian et al., 2012; van Oudenhoven et al., 2012).

Quantification and valuation of ES are needed to develop a framework for assessing ES from LUCC and to achieve the aims of land management plans (de Groot et al., 2010). These integrated assessments of LUCC and ES usually adopt several methodologies such as spatial mapping, economic valuation and simulation models (de Groot et al., 2010). Spatial mapping is an approach to visualize the distribution of LUCC and ES to improve the recognition of ES as a useful policy support tool for sustainable management (Burkhard et al., 2009, 2012; Daily and Matson, 2008). Although this approach helps decision makers aggregate complex information on LUCC and ES, it is not clear what the optimal scale for mapping ES in regional systems is (Burkhard et al., 2012; Turner and Daily, 2008) and there is a limited adoption of socio-economic information (Kienast et al., 2009). Economic valuation is the monetary estimation of the provision of ES for human societies in order to compare ES economically, such as cost-benefit analysis (Repetto et al., 1987; Daily et al., 2000; Arrow et al., 2004; Daily et al., 2009). However, the monetary estimation may overlook some ES, which are difficult to estimate in monetary terms and environmental and social aspects (Daily et al., 2009; de Groot et al., 2010). Models simulate change and quantify a spatio-temporal status of LUCC and related ES in specific regional systems and estimate the impact of environmental and human factors on ES (Briner et al., 2012; Grêt-Regamey et al., 2012, Huber et al., 2013). Although these models can reflect complex characteristics of the environmental systems, they normally focus on specific ES and are sensitive to the spatio-temporal scale of the systems (de Groot et al., 2010). To overcome the disadvantages and capitalize on the advantages of these approaches, they can be combined in an integrated framework. This thesis suggests integrated modeling framework, which simulates spatial changes of LUCC and their impacts on ES under the hydrological aspect of water quality at different scales of a mountainous watershed area, which could be adopted as a policy support tool.

1.1.3 State-of-the-art and research gaps

1.1.3.1 Introduction: framework of land use change and ecosystem services

Because there are several challenges when analyzing LUCC and ES as mentioned above, it is necessary to develop a modeling framework to estimate the effects of LUCC on ES (Ostrom, 2009; Posthumus et al., 2010; van Oudenhoven et al., 2012). These modeling frameworks is developed to estimate ES with a comprehensive understanding of regional systems. A framework is a structure which simulates the assessment of ES provisions on various spatial scales as a consequence of LUCC through selected ES indicators (Carpenter et al., 2009; van Strien et al., 2009; Niemeijer and de Groot, 2008; de Groot et al., 2010; Layke et al., 2012; van Oudenhoven et al., 2012). This type of framework provides a systematic understanding and quantification of regional environmental systems including LUCC and ES and thus it could be applied in decision-making processes for sustainable development (Layke, 2009; van Oudenhoven et al., 2012). To develop an integrated modeling framework, it is necessary to understand the current status of LUCC and ES models, which provide simulation outputs through an integrated modeling framework in mountainous watershed ecosystems.

1.1.3.2 Simulation models of land use changes

Simulation models are a useful approach to estimate spatial changes of LU by coupling human and environmental systems, thus capturing their complexity (Verburg et al., 2004b). The model estimates spatio-temporal ES and trade-offs among ES as a result of LU management in the context of interactions between social and environmental systems (Seppelt et al., 2011). Simulations of LUCC models are combined with various scenarios for environmental management planning (Verburg and Overmas, 2009). These models apply different techniques and approaches to simulate LUCC resulting from spatio-temporal LUCC patterns and factors (Meiyappan et al., 2014). LUCC models adopt statistical or process-based approaches to simulate interactions between human and environmental systems (Turner II et al., 2007). Among various modeling approaches, Cellular Automata (CA) and Agent-based models (ABM) are widely used to simulate spatio-temporal LUCC processes, which reflect complex and emergent characteristics of LUCC. CA is a bottom-up approach which simulates the status of spatial cells in a given time step, which is suitable for the development of LUCC models (White et a., 2000; Verburg et al., 2004b). CA-based LUCC models are commonly used in LUCC studies because they reflect complex aspects of changes using transitional rules based on a mathematical framework (Clarke et al., 1997). ABM is also a computation model, which simulate the status and decisions of agents' behaviors resulting from their interactions with other agents and the system environment (Ferber, 1999; Matthews et al., 2007). ABM is adopted into LUCC studies since it allows simulating the effects of human decision-making and interactions with other on the spatial distribution of LUCC (Brown et al., 2005; Matthews et al., 2007). Because both modeling approaches consider the spatial distribution of LUCC and can handle uncertain and complex characteristics of LUCC, they can easily be combined with spatial assessment models of ES.

However, development of these modeling approaches is accompanied by uncertainty and accuracy problems of model outputs. The uncertainty of LUCC model results arises in various ways during the development of LUCC models (Pontius and Neeti, 2010). Although these simulation methods reflect interactions between human and environmental systems, limited knowledge of real-world processes inevitably generate uncertainty (Pan et al., 2010; Ligmann-Zielinska et al., 2014). In CA models, these uncertainties arise from influences of individual stakeholders' decision as well as the spatial scale of input and output of models, such as data resolution and neighborhood configurations (Pan et al., 2010). To solve these problems, different scales need to be considered in a modeling framework and an understanding of neighborhood interactions is also needed. ABMs can reduce uncertainty about stakeholders' interventions but they also have the same problems regarding spatial scales and understanding of real-world processes. This could be resolved by an uncertainty and sensitivity analysis of model outputs, which reveal the influence of LUCC driving factors and their interactions on model outputs (Ligmann-Zielinska et al., 2014). Through these steps to control the uncertain influence of the model outputs, a well-designed and sophisticated estimation of ES from the simulation results of LUCC is possible. Because integrated modeling frameworks could validate model outputs with quantitative indicators (Bockstaller and Girardin, 2003; Niemi and McDonald, 2004; van Oudenhoven et al., 2012), LUCC models are integrated into the modeling framework using various validation approaches according to model types.

1.1.3.3 Assessment of hydrological ecosystem services

Hydrological ES in mountainous watersheds (e.g. fresh water provision and water quality regulation) are related with other ES and LUCC within dynamic and complex systems (Brauman et al., 2007). Selection of indicators and analysis to assess these ES is essential for the development of a modeling framework because these indicators need to be able to accurately estimate provisions of regionally important ES under LUCC as well as trade-offs between ES as a result of regional planning (de Groot et al., 2010; van Oudenhoven et al., 2012). Assessment of hydrological ES is combined in various ways with quantification and visualization tools of these services and with hydrological models (Vigerstol and Aukema, 2011). Among them, the Soil and Water Assessment Tool (SWAT) is widely applied to assess and quantify hydrological ES (Arnold et al., 1998; Neitsch et al., 2009; Vigerstol and Aukema, 2011; Logsdon and Chaubey, 2013), which reflect complex processes in water systems and to estimate changes in hydrological ES as a consequence of LUCC. Because SWAT can estimate temporal changes of hydrological ES at both watershed and sub-watershed levels, the model can estimate the regional importance of hydrological ES (Vierstol and Aukema, 2011). As mentioned above, spatial scale is essential when estimating and developing a model system of LUCC and ES. Application of SWAT can resolve the problems of spatial scales of ES in hydrological systems. As concerns about the importance of LUCC and hydrological ES are growing, several studies develop integrated models both to simulate LUCC and specific at ES in the regional scale. Regulation of soil erosion is a significant hydrological ES in watershed regions and is strongly affected by soil retention, which itself results from regional spatial and temporal LUCC (Fu et al., 2011). In particular, agricultural practices cause changes of regulation of soil erosion control because the magnitude of soil retention varies by vegetation type (Arnhold et al., 2014) and status of agricultural LU, such as cultivated or abandoned (Kosmos et al., 2000; Jain et al., 2001). Therefore, assessment of soil erosion could be improved through evaluation of soil erosion control ES under LUCC. (Fu et al., 2011). The Revised Universal Soil Loss Equation (RUSLE) model by Renard et al.(1997) is widely applied to estimate annual soil erosion rate based on changes of vegetation status under various LU scenarios (Angima et al., 2003) and thus RUSLE is frequently used to simulate and predict spatio-temporal changes of soil erosion (Angima et al., 2003; Kouli et al., 2009; Yang et al., 2003). Because RUSLE simulates spatio-temporal changes in soil erosion rates under LUCC, the model can be integrated with LUCC models.

1.1.3.4 Integrated models of land use change and ecosystem services under different land management scenarios

These integrated models of LUCC and ES simulate spatial and temporal LUCC and assess changes in ES resulting from interactions between human and environmental systems on a regional scale. Assessment of ES provision using suitable indicators at optimal scales is a significant step towards incorporating ES due to regional LUCC into a modeling framework (van Oudenhoven et al., 2012; Burkhard et al., 2012). To quantify and assess ES under LUCC, some modeling frameworks are widely adopted, such as the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) (Tallis and Polasky, 2009) and Artificial Intelligence for Ecosystem Services (ARIES) (Villa et al., 2009). Although these models are widely applied in ES research, improved quantification of ES is needed to reflect the complex characteristics of ES in a modeling framework (de Groot et al., 2010; Logsdon and Chaubey, 2013). The importance of LUCC for ES has led to research on estimation of ES under LUCC, which focused on specific ES at a regional scale, such as pollination services (Kremen et al., 2007), carbon storage (Wu, 2003), water resource (Baker and Miller, 2013), biodiversity (Martinez et al., 2009) and local climate change (Pielke et al., 2002). On the other hand, integrated estimation of ES and trade-offs between different ES with various assessment tools were also developed and adopted into ES research (Polasky et al., 2011). In particular, CA models are widely combined with hydrological modeling to estimate spatial changes of water-related ES as a result of LUCC (Deng et al., 2015; Kim et al., 2013; Marshall and Randhir, 2008; Memarian et al., 2014; Park et al., 2011; Zhang et al., 2013). ABM are also used to estimate specific ES such as carbon storage (Robinson et al., 2013), species habitat and biodiversity (An et al., 2006; Brady et al., 2012), runoff control (Bithell and Brasington, 2009) and pollination services (Kremen et al., 2007) under LUCC.

Several studies have tried to estimate effects of land management plans on regional LUCC and provision of ES using modeling frameworks. Portela and Rademacher (2001) developed a model of forest-related LUCC and valuation of regional ES under payment of ecosystem services (PES) scenarios. Chan et al. (2006) estimate the spatial distribution of changes in ES due to LUCC from diverse conservation plans. Egoh et al. (2008) evaluated ES spatially and extracted hotspots of ES provision for management planning. Brady et al. (2012) adopted ABM to simulate the spatial allocation of agricultural LU under different agricultural policies and estimate ES from LUCC. Nelson et al. (2009) developed a spatial model of LUCC and their impacts on the provision of ES with InVEST under urban and crop expansion scenarios. Lawler et al. (2014) simulated spatial LUCC from econometric models and their impacts on provision the of ES under future LU policies for management of different ES in the United States. Van Oudenhoven et al. (2012) developed a modeling framework of effects of land management plans on 9 selected regional ES. For water-related ES, Fürst et al. (2010) developed a planning support tool, called GISCAME, for spatial assessment of LUCC and ES. This model was applied to assess hydrological ES in a watershed in Western Brazil under different types (development and conservation) of land management plans (Koschke et al., 2014) and a watershed in Germany under different agricultural land management (Frank et al., 2014).

Although several studies have considered the effects of land management policies on conservation or development of land resources, they have so far neglected different types of instruments in land management policies to accomplish management purposes. Land management plans, especially for environmental conservation, are applied to different policy instruments such as PES and command-and-control regulations (Engel et al., 2008). Although these policies have different approaches, the efficiency of policy instruments is still not considered for ES management issues (Engel et al., 2008) and it is difficult to estimate policies due to lack of criteria (Goulder and Parry, 2008), scale mismatches between political and ecological scales for valuation of ES (Turner and Daily, 2008; Luck et al., 2009) as well as scales of policy adoption on ES (Newig and Fritsch, 2009).

1.1.3.5 Multiple scales on model development

When developing an integrated modeling framework, spatial and temporal scale should be considered at all stages as mentioned above. Scale is an analysis dimension of a specific system under a given spatial, temporal, quantitative or analytic aspect (Gibson et al., 2000; Verburg et al., 2004b). The spatial and temporal scale is essential to develop simulation models on LUCC because LUCC patterns vary by spatial scale and thus driving factors of LUCC also vary (Verburg et al., 2004b). Assessment of ES is also sensitive to scale issues such as spatial scale in mapping ES (Burkhard et al., 2012; Turner and Daily, 2008), estimation of ES indicators and trade-offs between ES (de Groot et al., 2010; van Oudenhoven et al., 2012), spatial and temporal boundaries of environmental systems with complex and emergent phenomena (de Groot et al., 2010) and spatial range of policy analysis and instruments (Turner and Daily, 2008; Luck et al., 2009; Newig and Fritsch, 2009). Although finding the optimal scale is essential to develop well-designed models and understand the relationship between LUCC and ES, optimization of scale is difficult under when understanding of regional systems is limited. To solve these scale problems, modeling frameworks should consider multi-scale systems (de Groot et al., 2010; van Oudenhoven et al., 2012). Consideration of scale could be expanded to consider hotspot areas of ES where severe degradation has occurred (Egoh et al., 2008). Because hotspot areas often have different patterns with entire system boundaries, assessment of ES under different spatial scales, which consider both entire systems and hotspot areas, could reflect LUCC and ES within a modeling framework.

1.1.3.6 Model development

Modeling frameworks have recently been applied to explain interactions between human and environmental systems, from properties of the natural environment to policy analysis (van Oudenhoven et al., 2012). In the previous chapter, several approaches to estimating LUCC and ES were described, which have been applied separately in specific analyses or collectively in integrated modeling approaches. However, as ICSU (2008) and de Groot et al. (2010) pointed out, integrated modeling frameworks of LUCC and ES cannot reflect effects of management plans and decision-making on the provision of ES because those approaches cannot quantify values of ES under different management directions at regional scales. Therefore, the modeling framework is adapted to assess LUCC impacts on ES under different land management scenarios in this thesis.

1.1.3.7 Research gaps

Although integrated modeling, which combines models of LUCC and assessment of ES, is widely used to quantify regional impacts of LUCC and their effects on ES, these modeling approaches could not capture LUCC and changes in ES resulting from by human land use decisions.

Lack of understanding of mountainous LUCC

Understandings of LUCC in mountainous areas are rarely considered in LUCC research despite their importance for the provision of regional ES. LUCC patterns and factors need to be identified to understand LUCC and develop LUCC models in mountainous areas with high socio-ecological heterogeneity.

Development of spatial models to simulate LUCC and ES in mountainous watersheds

Although several studies focused on the role of mountainous watershed areas, spatial simulation models of LUCC and ES are deficient to understand spatially different impacts of LUCC on regional ES. Integrated modeling frameworks for LUCC and ES could simulate LUCC and ES at different spatial scales in the mountainous watershed areas and help to understand these systems.

Estimation of impacts of different types of policy instrument on regional ecosystems

Although many researchers investigated different environmental policy scenarios, efficiency between direct regulation and PES policy instruments are still questionable. Comparisons of various policy scenarios could be useful to find which policy instruments are useful in each region and to understand the advantages and disadvantages of different conservation policies.

Spatial models of farmers' decision-making processes and their impacts on water quality

Although earlier farmers' decision-making models tried to simulate their decision, these simulation models considered spatial aspects to a lesser extent. As spatial ABM is therefore adopted to reflect these factors in the model, to simulate spatio-temporal changes of LUCC and quantify soil erosion.

1.1.3.8 Description of modeling framework

Figure 1, which is adopted from Oudenhoven et al. (2012), shows which elements and processes of the modeling framework for LUCC and ES used in the thesis, such as driving factors, ecosystem components, service provision, human society and response. Driving factors influence ecosystem properties directly or indirectly through LUCC; in turn, ecosystem properties affect ecosystem functions (MA, 2005; van Oudenhoven et al., 2012). Through a set of ecosystem functions, ES are provided to human society (Kremen, 2005). Human society derives benefits from ES and the impacts of these benefits are assessed by quantitative indicators (Nelson et al., 2009; van Oudenhoven et al., 2012). Through quantitative assessment of ES, stakeholders can change their perception of ES and these changes are applied in policy and decision-making processes (Fisher et al., 2009). In the framework, direct effects are represented as dotted lines and feedbacks are represented as dash lines.

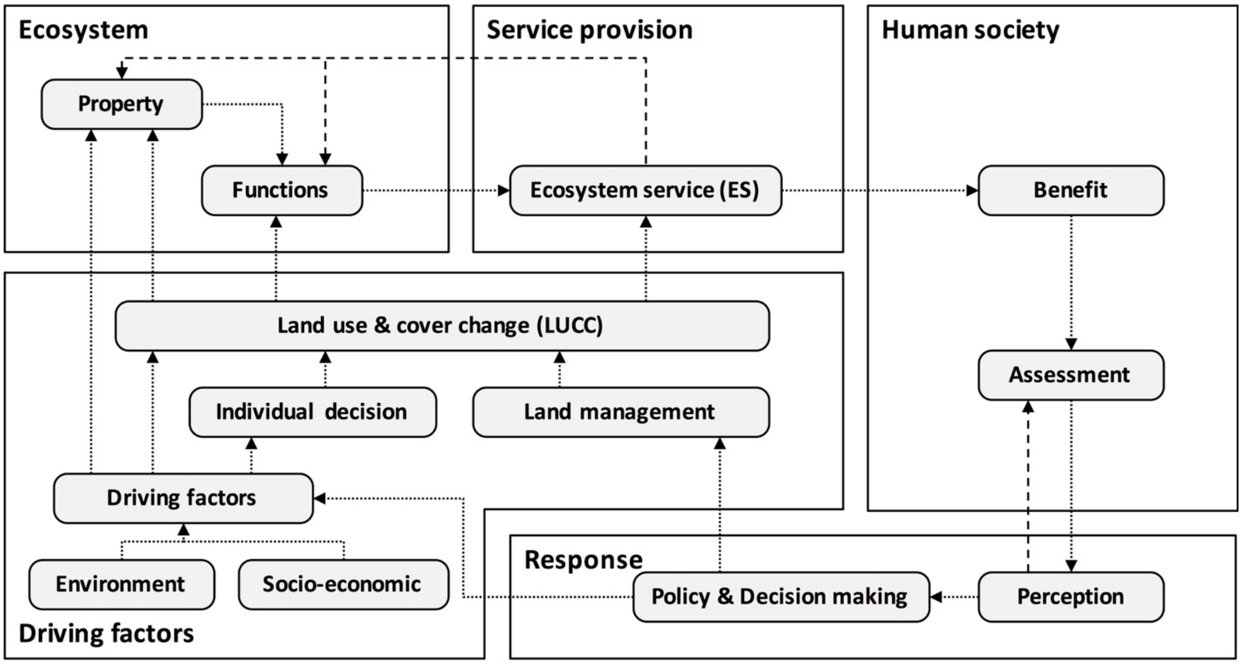

Figure 1. 1 An Integrated framework for assessing processes linking impacts of land use changes and ecosystem services to human society.

1.2 Overview of this thesis

1.2.1 Objectives and hypotheses.

To understand LUCC processes and to simulate possible LUCC and resulting changes of ES under different management scenarios, the development of a modeling framework is a useful tool for quantitative simulations within environmental systems. The overall goal of the thesis is to develop a modeling framework which reflects the uncertainty and complex features of LUCC and the response of ES. The specific objectives of this thesis are: (a) to quantify LUCC patterns and their natural-environment al and socio-economic driving factors; (b) to simulate LUCC and ES under different policy options through a combined modeling framework of CA and hydrological modeling; and (c) to simulate agricultural LUCC and ES via ABM reflecting farmers' decision-making processes in one hotspot sub-region of the research area.

Study 1: Driving forces of archetypical land-use changes in a mountainous watershed in East Asia

Quantifying spatio-temporal LUCC patterns and their driving factors is necessary to understand LUCC processes. Multinomial logistic regression (MNL) analysis was used to identify LUCC factors in the Soyang River Basin area in archetypical periods. Neighborhood land use factors were used to supplement understanding of LUCC, while socio-ecological underlying factors were revealed as explanatory factors, as well as to develop integrated LUCC models for estimation of LUCC and ES.

Study 2: Land use change and ecosystem services in mountainous watersheds: Predicting the consequences of environmental policies with cellular automata and hydrological modeling

LUCC in mountainous watersheds affects regional ES by controlling water quality in the downstream areas. Understanding the complex characteristics of LUCC processes and simulating LUCC is necessary to supplement regional environmental policies. Integrated modeling framework was developed, which combines CA with hydrological modeling to simulate LUCC and ES. This framework was applied to estimate regional impacts of different types of environmental policy scenarios based on PES and/or command-and-control regulations.

Study 3: Simulation of agricultural land-use changes and ecosystem services in a mountainous agricultural region using an agent-based model (ABM)

Farmers' decision-making about agricultural land uses and crop choices affect regional land systems and ES. In particular, farmers' decisions have emergent characteristics, which lead to different responses to policy directions depending on policy types. In such situations, understanding farmers' decision-making processes is necessary for devising management plans to maintain regional ES. To better understand farmers' decision-making processes, an ABM was used to simulate possible changes of farmers' agricultural LUCC under various factors and scenarios.

1.2.2 Study area

The study area of this thesis is located in the Soyang River Basin (127' 43" to 128' 35" E and 37' 41" to 38' 29" N), in the north-eastern part of South Korea close to the border with North Korea (Figure 2). This river flows into the Han River, which is the biggest river in South Korea and flows across the Seoul metropolitan area. The river is regarded as significant by a national government for environmental reasons, due to geographical features of the river area. Because the Soyang River is significant water source for residents in the Seoul metropolitan area, its water quality and quantity are important issues to secure stabilized water resource. To protect water resource for residents and industry, the government constructed the Soyang Dam at downstream of the river prior to its confluence with the Northern Han River in 1974. After dam construction, various regulation policies were adopted for environmental reasons to maintain water quality in the Soyang Lake, which is formed by the dam (Kim, 2006). The basin area of the river is a mountainous region with forest covering as much as 89% of the area. Forest is mainly public forest and thus it is strongly regulated by multiple regulations (Kim, 2006). The rest of the region is mainly covered by agricultural areas, with rice paddies covering 1.8% and dry fields covering 4.1% of the basin area. Agricultural area is located in riverside and highland areas. Urban area only covers 1.2% of the watershed, mostly downstream of the dam, and belongs to Chun-cheon city, the biggest city of the province.

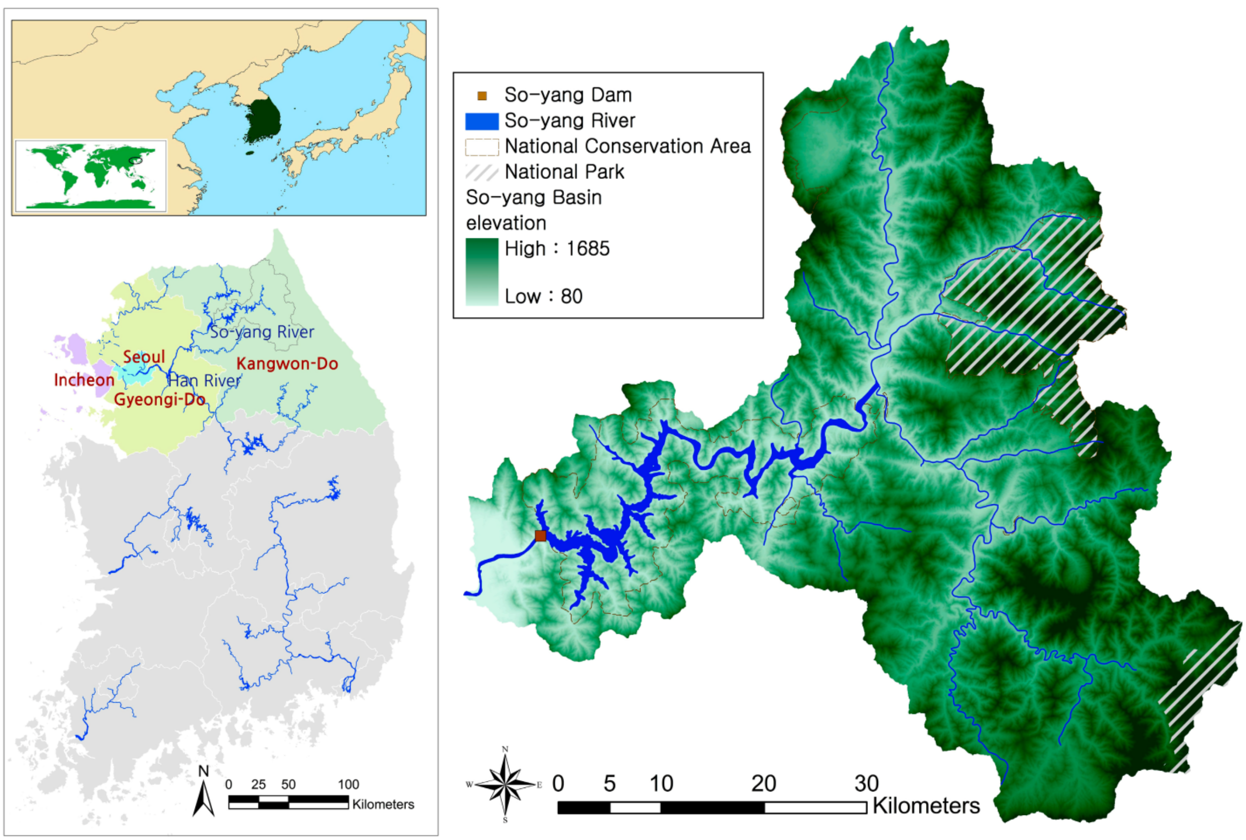

Figure 1. 2 Research areas considered in this thesis

Due to various constraints, land use for agricultural activities is concentrated in riverside areas which lack regulatory constraints. These limitations have led to a decrease in regional population and eventually a decline of regional economies in upstream areas of the basin, while urban areas expanded and tourism facilities grew in downstream areas. Residents in upstream areas immigrated to urban areas causing farmland fragmentation and abandonment (Yun, 2010). In this situation, highland agriculture in upstream areas was mainly cultivated commercial annual crops like cabbages, radishes, and potatoes as the main agricultural products. However, highland agriculture caused water pollution and devastation of the ecosystem due to soil erosion and chemical fertilizers, which worsened during monsoon periods and extreme rainfall events like typhoons, as experienced in 2006 (Lee, 2008; Park et al., 2011). In particular, highland farmland expansion via forest reclamation worsened soil erosion and increased environmental vulnerabilities in some agricultural sub-regions, which are called hotspots of water pollution (Park et al., 2010).

After water quality problems became public concerns, national and regional governments adopted environmental policies to reduce water pollution, such as organic and perennial crop promotions and reforestation in marginal agricultural farmlands (Poppenborg and Koellner, 2013). However, these policies had unexpected effects such as the growth of abandoned farmlands instead of other perennial crops (Jun and Kang, 2010). Moreover, there have been various types of environmental policies, which have different policy effects according to regional characteristics. In the current situation, it is necessary to understand LUCC processes and to estimate possible impacts of different policies to inform the policy making process.

1.2.3 Methods

1.2.3.1 Development of land use simulation models

Simulation modeling approaches were adopted to answer research questions to understand LUCC and impacts of environmental policies. These simulation models were developed as spatial models based on spatial data as tools to understand LUCC processes under different policy scenarios. Different simulation modeling approaches were adopted according to the spatial scale considered and according to data availability in the Soyang River Basin. A CA model was used to simulate LUCC in the Soyang Basin areas because CA reflects spatial interactions of LUCC as spatial and temporal simulation models based on mathematical transitional rules (Verburg et al., 2004a). In Haean catchment, an ABM is adopted to simulate agricultural LUCC based on farmers' decision, which reflects interactions of individual agents and their own decision-making processes (Clarke, 2014).

To develop simulation models of LUCC, it is necessary to extract possible LUCC factors and their quantitative relations with LUCC (Verburg et al., 2002). MNL is widely used in land use studies to extract LUCC determinants, which estimates probabilities of LUCC and the effects of driving factors as explanatory variables (Rutherford et al., 2007). MNL estimates probabilities of LUCC and the intensity of driving factors as explanatory variables. The probability functions are described by $P_{ij} = exp(\beta_i X_j)/\sum_{k=1} exp(\beta_i X_k)$. P is the probability of LUCC from land cover (LC) i to j, where k denotes the LC classes, β is a vector of estimation parameters and X are vectors of independent variables. To reflect human-environmental interactions, there were various independent variables (biophysical, distance, neighboring land use, regulation policy, population) to estimate driving factors of multi-directional LUCC for the main land use types (urban, forest, agriculture) across 10years of changes. Among these variables, neighboring land uses were estimated by functions of enrichment factors (EF) reflecting neighborhood interactions, as proposed by Verburg et al (2004a). The EF reflects the levels of spatial concentration of specific land types in the entire area, thus it can find optimal neighborhood boundaries (Verburg et al., 2004a). From the MNL and neighborhood EF, the CA model of LUCC was developed. Moreover, underlying LUCC factors were also extracted, which are difficult to estimate from statistical analysis, from literature reviews and stakeholders' interviews to understand socio-economic determinants of regional LUCC to construct possible policy scenarios for the simulation models.

CA-based LUCC models simulate the status of the cells in a land grid based on cellular dynamics reflecting the spatial interactions of cells (Verburg et al., 2004a). CA models consider the status of cells, neighborhood interactions, the initial conditions of cells, and the status of cells when they change (Clarke, 2014). Each cell has a transitional probability function from land type i to j in a simulation time step as $S_{ij}^{t+1} = \int(S_{ij}^{t}, \Omega_{ij}^{t}, Con, N)$, where S is the status of the cell including local probabilities, Ω is the neighborhood evaluation function, Con is a factor constraining changes, N is the number of cells (Feng et al., 2011). Local probabilities are calculated from MNL and boundaries of neighborhood evaluation functions are set where EFs have the highest values. Constraint factors are considered in the phase of policy implementation for environmental policies to control agricultural expansions. The framework of CA model was implemented using NetLogo 5.3.1 software packages and simulate the model from 2006 to 2056 over 10 year periods under various environmental policy options (business as usual, forest protection, reforestation policy on marginal agricultural lands, mixed policy). Before running the model, calibration and validation the CA model were progressed with a three-map comparison method, which compares actual land use maps of 1995 and 2006 to a simulation result map of 2006 to quantify model accuracy (Pontius et al., 2008).

Since farmers' decision-making is more affected by personal characteristics, ABM approaches were adopted to develop farmers' agricultural LUCC models in the Haean catchment as a hotspot of water pollution. ABMs simulate agents' behaviors and interactions as well as the induced complex phenomena they induce within the system environment (Sun and Müller, 2012). ABMs specify agent types, decision-making processes, learning or adaptive rules, agents' behaviors, and system boundary (Clarke, 2014). Individual farm households were used as agents and their characteristics were based on survey results of farmers' attitudes toward ES and socio-economic status, which was conducted by Poppenborg and Koellner (2013). The survey data was combined with spatial data to estimate decision-making processes using MNL and decision trees as decision-making heuristics. To develop adaptive rules from agent interactions', opinion dynamics and bounded confidence (BC) models were adopted (Hegselmann and Kraus, 2002). BC models reflect that agents tend to interact with agents whose opinions differ only slightly, called a BC situation (Kou et al., 2012). All agents connect with each other inside the system boundary, called small world network, and have higher connections with neighboring agents and lower connections with outside agents (Watts and Strogatz, 1998; Costa et al., 2006). The model was validated using an uncertainty and sensitivity analysis, which estimated the uncertainty of the ABM in reflecting complex human-natural systems (Ligmann-Zielinska et al., 2014). The ABM was also developed using NetLogo software, which simulates annual decisions about farmers' agricultural land use (rice, annual, perennial and fallow) for 10 years under different land use scenarios. Variance-based sensitivity analysis (VBSA) were used to estimate model performance variations in driving factors by estimating the contribution of individual and/or a combination of input factors (Ligmann-Zielinska et al., 2014). The sensitivity result of the model tested various model outputs within the simulation boundaries and found the contribution of input factors on model outputs (Ormerod and Rosewell, 2009).

1.2.3.2 Estimating ecosystem services under different modeling approaches

LUCC in mountainous areas affects regional ES such as regulation of soil fertility and water provision while providing crop and bioenergy production (Schröter, 2005). In Soyang River Basin, which has undergone dynamic LUCC such as deforestation/reforestation, agricultural expansion around upper stream areas and urban expansion in downstream areas, agricultural LUCC is a significant cause of water pollution.

In the following step, models of LUCC and of ES were combined in the CA model for spatial simulations of LUCC with SWAT model for estimating ES related to hydrological cycling. The model first simulated possible LUCC under various policy scenarios to derive land use maps from the CA model, which were then used as input into SWAT. The SWAT model used various variables such as topographic, soil, and climate data, as well as interviews and investigation data from a field survey about land management (Arnhold et al., 2014; Shope et al., 2014). We quantified model uncertainty using a Sequential Uncertainty Fitting (SUFI-2) optimization algorithm (Abbaspour et al., 2007), which is also used to perform calibration and validation of the SWAT model. Once the model is set from data for the baseline period in 2006, which is also used as the initial period of a model simulation, we estimated changes in hydrological attributes until the year 2056. From this model, we simulate changes of regional ES like the quantity of water supply from water yield, soil erosion from sediment estimation and water quality from an amount of nitrogen (N) and phosphorus (P) loads reflecting uses of fertilizers on agricultural lands. The results quantified each related index for N, P and soil sediments for daily time steps, which were finally summarized to give annual results. We focused on changes of ES for the whole watershed area and in two agricultural hotspot areas to compare environmental policy impacts of different policies on spatial scales.

In comparison with the combined CA and SWAT modeling framework, we developed one integrated model to simulate agricultural LUCC and soil erosion in the ABM framework. This integrated model based on spatial simulation has the advantage of estimating ES systematically (Kubiszewski et al., 2013). We adopted the Revised Universal Soil Loss Equation (RUSLE) to estimate the annual rate of soil erosion per unit area, especially from agricultural land use (Renard et al., 1997). Annual soil erosion is estimated from rainfall (R), erosion (K), slope-length and slope (LS), vegetation-cover (C) and support-practice (P) factors. Among them, a spatial distribution of vegetation and support-practice factors are changed from the results of agricultural LUCC and others were estimated from currently available data.

From this model, we simulated annual soil erosion rate resulting from agricultural LUCC for next the 10 years.

1.3 Main results

Dominant patterns of LUCC are urban expansion in downstream regions, agricultural expansion in highland agricultural regions, contrary to decrease in other regions. Urban areas have increased steadily in downstream regions due to urban sprawl, resulting from deregulation of development restriction zone. Agricultural areas have increased in highland agricultural regions due to highland agricultural promotion policies since the 1980's. Overall agricultural expansion progressed from 1980-90; in contrast, reforestation was advanced in 1990-2000. Results of MNL indicated an explanatory power of the independent variables for different land use types in the two sub-periods. LUCC was mainly affected by slope and neighboring land composition in all land types. In comparison to other land types, agricultural land is more affected by rainfall and regulation (national conservation zone).

After extracting LUCC factors and neighborhood extents, we developed the CA model to estimate LUCC and ES under different policy scenarios across 50 years. The model was validated by comparing simulation maps and actual land use maps of 2006 to estimate the accuracy of simulation results and it turned out that the model had acceptable simulation accuracies compared to other CA models. In all scenarios, there were similar patterns of reforestation in marginal agricultural areas regardless of policy types. However, the magnitude of reforestation is affected by the policy type. In particular, current management scenario (NO) results in a 0.8% increase in forested area, while in the combined policy scenario of Reforestation and Protection (R+P) forest area increased by 2.5% by 2056. Dry fields decrease by 5% in the NO scenario, while they decrease by up to 43% in the R+P scenario, reflecting different impacts of types of policy interventions, whereas rice paddies decrease similarly regardless of policies. With respect to policy impacts on the hotspot regions, dry fields areas increase by 18% in the NO scenario while they decrease by up to 31% in the R+P scenario. When we used the result to estimate water related ES, differences in water qualities are found. Sediment and P and N loads vary by policy type, unlike stable maintenance of water yields. While there was a decrease by up to 8% in sediment, 3% in total N and 1% in total P in 2056 without policy interventions, the combined policy decreases sediment by 48%, total N by 21% and total P by 30%, reflecting strong impacts which could help to maintain regional ES.

From the simulation of LUCC using the CA and SWAT framework, it can be concluded that LUCC in hotspot areas drive the impacts in the whole Soyang Watershed. We, therefore, adopted an ABM for Haean catchment, a dominant source of water pollutants, as a case study. We extracted influences of individual and combination values for each simulation output from a VBSA, which indicated that spatial characteristics of farmlands and farmers' attitude toward water quality were a significant factor for perennial crops while the factor less influenced to annual crops. We simulated agricultural land use and soil erosion rates under different land management scenarios and compared spatial patterns of agricultural LUCC and soil erosion rate under different land management scenarios. Results showed that farmers with large-sized farms converted their lands to perennial crop farms less, whilst maintaining current field status (rice and annual crops), resulting in a moderate decrease in soil erosion. In fallow land expansion scenarios, fallow lands expanded by up to 7% of the research areas, increasing soil erosion rate by 6%, which reflects that fallow land expansions do not change annual soil loss more than expected although fallow lands have highest P-factor in RUSLE. In two different fallow land management scenarios (ginseng farm and perennial crop expansions), the ginseng farm expansion scenario is more effective at reducing soil erosion than perennial farm expansions. However, the magnitude of the reduction of soil loss is also lower, although fallow lands and annual crop areas decreased.

1.4 Discussion

1.4.1 Estimation process of regional LUCC and ES within modeling framework

We identified patterns and driving factors of LUCC for two sub-periods in paper 1. The first decade (1980-90), characterized by agricultural growth and deforestation, was affected by land development plans, including dam and highway constructions corresponding to results from the MNL, such as the impact of rainfall and biophysical factors on agricultural land conversions. Agricultural areas are affected by rainfall, which are in turn related to regional climate changes, by dam construction and by the monsoon period during summer, corresponding to hydrological aspects of the region (Kim, 2012). Elevation and slope have negative effects on agricultural areas, reflecting agricultural land abandonments in mountainous marginal farm lands, a common phenomenon globally (Pingali, 1997; McDonald et al., 2000). In a similar context, forest expansions occur in areas with lower accessibility which worsen agricultural conditions. Distance factors are less significant because LUCC occurred in riverside; areas at a distance from the river and urban areas are maintained as forest, without land transitions. Existing land regulation policies had different effects on LUCC depending on the policy objectives. Because designations of national parks in South Korea have the twin aims of natural conservation and tourism promotions (Lee et al., 1998), urban growth from forest areas in the national park could be explained as expansions in tourism facilities while agricultural areas reduced. As for national conservation areas, which aim to protect regional natural ecosystems and resources, the regulation led to decrease in agricultural LUCC due to a restriction of land use activities (Kim, 2006). Forest expansion in agricultural areas was more influential in neighboring forest areas, reflecting natural conversions of abandoned farms. In contrast, deforestation near agricultural and urban lands also occurred in the region, and stemmed from an expansion in highland agriculture which removed marginal forest on areas with lower slope and elevations.

The later period (1990-2000), which saw some reforestation, has similar explanatory factors although different LUCC patterns were found. Agricultural area was converted to forest in higher summer rainfall areas to prevent flood damage (Kim and Lee, 2011). As for topographical factors, there is a different tendency compared to the earlier period, reflecting agricultural expansion in gentle sloped and smooth mountainous areas for highland agriculture, especially in the hotspot areas. In response, forest growth occurred at areas with higher elevation and slope within the boundary of natural conservation areas. Distance, neighborhood and regulation policies had patterns similar to those of the earlier period.

After extraction of LUCC driving factors and scenario development, we developed a model framework to combine CA and SWAT to estimate LUCC and water-related ES under different implementation of conservation scenarios in paper 2. We found that urban expansion is a common phenomenon regardless of policy instrument after deregulation of development restriction zones for local development plans (Jeon et al., 2013). The decrease in rice paddies is slow because they are cultivated in suitable agricultural areas that are not targets of conservation policies. Unlike rice paddies, dry fields are mainly located in steep slope areas, which are target areas of conservation policies. All policies enhance water-related regulating ES (soil erosion and water quality) without trade-offs in provisioning ES (fresh water quantity) due to a maintenance of water balance in the region regardless of LUCC. However, we found different policy impacts on LUCC depending on the type of policy instruments. Increased erosion control and water quality stem from areas where the forest protection policy is in place rather than the reforestation policy. We also found that policy responses varied with spatial scale, especially in the highland agricultural sub-watershed which were hotspots of water pollution. Unlike the general pattern for the entire watershed area, with moderate forest regrowth and agricultural declines, two headwater catchments showed agricultural expansion, which decreases regulating ES. Efficiency of the policies is also different in those areas, while reforestation policy is more effective at restraining agricultural expansion and restoring water purification capacities and erosion prevention. When a strict protection policy (covering both reforestation and protection) is adopted, water-related ES are more significantly improved than under singular conservation policies, regardless of their spatial scale. Although our results demonstrate the efficiency of conservation policies, these policies have limited success in achieving conservation objectives. These policies result in only moderate improvement of LUCC and ES in the Mandae watershed, where the largest water quality degradation occurred than in another hotspot and across the entire watershed area. Although reforestation is more efficient than protection in the area as mentioned above, financial resources and farmers' participation are practical problems, which limit reforestation to 50 ha per year. To develop better management plans, it is necessary to concentrate reforestation incentives in the headwater catchment as a concentration strategy to improve policy efficiency.

After the development of a modeling framework for the watershed, we focused on farmers decision-making processes and agricultural LUCC in the Maendae stream area where most water pollution is generated. We develop an ABM of agricultural LUCC and crop choice based on farmers' and spatial characteristics and then we simulate annual soil erosion rate according to changes of agricultural LUCC in paper 3. When we integrated farmers' survey data, which was analyzed by Poppenborg and Koellner (2013), and spatial data, as driving factors of farmers' decision in model development, we found different driving factors of agricultural LUCC although we conducted the same MNL analysis, which leads to different simulation results. To control uncertainty of the ABM, we conducted uncertainty and sensitivity analyses to assess model performance for estimating driving factors (Ligmann-Zielinska et al., 2014). In our model, simulation for rice paddies has lower uncertainty than for other crops, which are located in suitable areas for agriculture and guarantee stable incomes (Jun and Kang, 2010). This was also found in sensitivity analysis: while rice paddies are sensitive to changes in policy factors (subsidy, capacity building program (CBP), and legal legislation), annual and perennial crops have higher uncertainty, while rice paddies have stable outputs. Farmers' attitudes toward water quality is the dominant factor for perennial crop choice, more than their attitudes toward soil erosion, which is different from findings in other research (Poppenborg and Koellner, 2013).

We simulated annual soil erosion rate resulting from farmers' crop choice as the spatial impact of agricultural LUCC on regional ES in areas where water quality is the most important environmental issue. The annual soil erosion rate is 32.7 ton/ha/year in the baseline scenario, which is higher than indicated by earlier research (Poppenborg, 2014). This is because our model included fallow land areas, which cause more severe soil erosion than in cultivated farmlands. Our results also indicated that perennial crops could not reduce soil erosion as effectively as we expected, which is different from Poppenborg (2014). Because estimation by RUSLE is based on the values of input factors, we adopted empirical results for the site from Arnhold et al. (2014). The values for C factors, which reflect land and crop types, did not varied with crop types and thus it estimates similar soil erosion rates regardless of crop changes. However, we did not have site-specific C factor values for fallow lands and ginseng farms although they are significant change factors for soil erosion (Lee and Jeon, 2009; Jun and Kang, 2010). Moreover, effects of ginseng farms on soil erosion are still problematic because ginseng farms, which are regarded as a mitigating factor (Lee and Jeon, 2009), could not reduce soil erosion due to lack of protection facilities on these farms (Cho, 2015). Because effects of ginseng farms on reducing soil erosion on the research site are still uncertain, we set higher variation values on ginseng farms, which increased the uncertainty of soil erosion results.

We applied an ABM based on different land management scenarios for the region and compared them to better understand spatial impacts of farmers' decisions on agricultural LUCC. We found that farmers' changes were not matched with a magnitude of spatial changes in the model although we did not include farm size in the model. Rice farmers with large farms tend to change their crops more than farmers with small farms, while annual crop farmers with large farms adhere to their current annual crops (Kim, 2014). Simulation results varied with fallow land management options, which caused more severe soil erosion than cultivated areas. Annual farms near forests were converted to fallow lands when we applied a scenario of farm abandonment by farmers with low capacity to maintain their farmlands (Rhee et al., 2009). Although the magnitude of fallow lands decreases in the catchment, fallow lands in marginal forests with steeped slope areas remain as fallow lands, which causes severe soil loss unlike other areas. Therefore, it is necessary to manage these marginal lands without agricultural activities, such as the reforestation policy, which focused on conversion of these marginal lands to forests. In the case of ginseng farm expansion, expansion of ginseng into marginal fallow areas reduced soil erosion and led to an expansion of perennial crops because of neighboring effects of farmers' crop decisions. However, adoption of ginseng farm expansions should be applied carefully because ginseng farms have uncertainty to reduce soil loss due to lack of management facilities.

1.4.2 Strengths and weaknesses of the modeling framework

We applied MNL to extract driving factors of LUCC from spatial data, which quantified the explanatory power of driving factors. However, this approach can not reflect underlying factors of LUCC. Apart from the driving factors of LUCC as quantified from MNL, there are underlying factors reflecting regional socio-economic characteristics. Because these factors are difficult to identify from a statistical analysis, we described these factors from literature reviews and qualitative research, which could be applied in policy scenarios (Abildtrup et al., 2006). Urban growth in the downstream area accelerated after deregulation and construction of roads and bridges to solve accessibility problems (Choi et al., 1998; Lee, 2009), which are not found in MNL with distance and neighborhood factors. Land abandonment stemmed from various factors after the Soyang dam construction. Soyang Lake worsened agricultural conditions by generating local climate change and increasing the logistic cost of agriculture (Choi, 2001). Unlike farmland abandonment in the areas near the lake, highland agriculture accompanied with deforestation in upstream areas has increased for economic and political reasons (Choi et al., 1998). Although MNL only reflects limited socio-economic and political factors in the analysis processes, it quantifies possible driving factors, which could be adopted into our modeling framework and applied as alternative scenarios into the framework. We tried to estimate impacts of LUCC on regional ES through the integrated modeling framework in paper 2 with alternative conservation policy scenarios to improve provisioning and regulating ES in the watershed. To reflect real world changes, we validated both CA and SWAT performance and then used both models to capture the spatial distribution of LUCC and their impacts on hydrological ES. Although our models still have output uncertainties due to large variability, they can reflect real-world changes from historical LUCC and water quality data. However, our models still have several problems such as limited incorporation of socio-economic LUCC driving factors and simplification issues in the model setup. Crop prices and farmers' perceptions are significant driving factors of agricultural LUCC (Lee et al., 2016), which were not considered here. Among various ES indicators, we only consider simplified water-related ES that cover fresh water provision, erosion prevention and water quality, which do not estimate other ES, such as food provision and their trade-offs with water-related ES (Maes et al., 2012; Nelson et al., 2009; Raudsepp-Hearne et al., 2010). Besides these, simplification of crop types into dry field areas due to a limitation of data and spatial scale, cannot reflect trends on complex crop portfolios such as expansions in fruit orchards or ginseng farms (Jun and Kang, 2010; Lee et al., 2016; Seo et al., 2014).

To solve limitations on farmers' decision-making and simplification of complex LUCC processes, we focused a hotspot sub-watershed and tried to develop a modeling framework for the decision-making processes and their effect on agricultural LUCC and soil erosion rate as a spatial response of LUCC. The model indicated the influence of farmers' individual decision-making based on personal perceptions and spatial characteristics of their farmlands. Because this model focused on the hotspot of water pollution, we could integrate farmers' decision-making processes into the model. We conducted a validation process with VBSA and used empirical data and values to develop a sophisticated model. However, our model still has several problems. We used land suitability index (LSI) values and farmers' intent for fallow land decisions, but we use the same the LSI function and value regardless of crop types. Additionally, we underestimate slope effects because we adopted criteria from earlier research, which mostly did not emphasize slope steepness. In a decision-module on farmers' crop choice, we do not reflect economic factors properly because our MNL functions did not show any explanatory powers for the money availability. Moreover, we only consider local farmers' decision-making and ignore land owners from outside the region, although land ownership is a significant driving factor of agricultural LUCC. To reflect the realistic LUCC in the region, decision-making process on the fallow and ginseng farm changes should be improved. Although we have several tasks that need to be performed to improve model performance, the model is useful to estimate spatial agricultural LUCC and soil erosion under different land management plans, which will help with the regional decision-making processes.

1.5 Conclusion

In this thesis, we developed a modeling framework to estimate LUCC impacts on regional ES under different land management policies in a mountainous watershed in South Korea. We found LUCC driving factors and neighborhood values and quantified explanatory powers on changes using the MNL method. From this analysis, we could explain spatial determinants of LUCC on major LC types. When we compared LUCC and their factors, we found causal relationships between LUCC and their factors. Furthermore, we found underlying factors of changes, which could not be extracted from statistical analysis. These extracted factors were used in simulation models of LUCC and then they were used to calculate transitional rules of LUCC models, while underlying factors are used to develop policy scenarios. We developed integrated modeling approaches, which combined LUCC and hydrological estimation of water-related ES. The model simulated and evaluated the efficiency of environmental policy instruments in a mountainous watershed. Although there are still several constraints, such as limited use of economic factors and simplification of ES and land use types, this modeling framework shows the efficiency of environmental policy instruments, primarily forest protection and reforestation policies to improve water-related ES in the region. Additionally, we focused on the sub-watershed where typical highland agriculture is conducted and water quality is severely degraded. We modeled the effects of individual farmers' decision-making processes on agricultural LUCC and estimated spatial impacts on regional ES under various land management scenarios. This model simulates spatial distribution of LUCC and their impacts on regional ES with respect to water-related issues. Agriculture and forest areas played an important role in improving or worsening water quality in the watershed area according to the simulation results of the model, and thus should be controlled by appropriate management plans. Environmental policies based on spatial regulation could encounter resistance from local stakeholders because the watershed areas are already heavily regulated for environmental and security purposes. As mentioned above, reforestation policies such as PES cannot achieve the aim of the policy, thus it is necessary to improve the range of the policy to match standards of local stakeholders. We need to better understand individual farmers' decision-making and their inducement to manage farmlands more environmental-friendly. However, we still left an application of economic factors in the model although these factors are important in farmers' decision-making. Environmental policies should, therefore, be accompanied by economic compensation for agricultural LUCC and technical approaches to prevent soil erosion at the farm level under current agricultural systems in the watershed. Additional research is necessary to find economically and environmentally sustainable policies and to manage trade-offs between human and environmental systems to strengthen the model. Because LUCC in the watershed result in environmental impacts on downstream areas as benefiting areas of ES (Liu et al., 2015), integrated approaches should consider areas beyond the boundary of the watershed environment. These modeling frameworks thus could expand their spatial scale and update individual decision-making and interactions with stakeholders, including farmers, in upper stream areas and agricultural customers in downstream areas.

1.6 List of manuscripts and specification of individual contributions

This thesis is composed of three studies, each in a separate manuscript. The first manuscript was published in the Journal *Land*. The second manuscript is submitted, and the third manuscript is being prepared for publication.

Manuscript 1 (Chapter 2):

Authors : Ilkwon Kim, Quang Bao Le, Soo Jin Park, John Tenhunen, and Thomas Koellner

Title : Driving forces in archetypical land-use changes in a mountainous watershed in East Asia

Journal : *Land*

Status : Published (2014)

Own and author contribution statement :

Own contribution : concept and study design 60%, data acquisition 90%, data analysis and figures 90%, discussion of results 80%, manuscript writing 70%

I. Kim, Q. Le, S.J. Park, J. Tenhunen, and T. Koellner designed the research; **I. Kim** collected research data; **I. Kim and Q. Le** analyzed the data and created figures and tables; **I. Kim, Q. Le and T. Koellner** interpreted and discussed results; **I.Kim** wrote the first draft of the manuscript; **I. Kim, Q. Le, J. Tenhunen and T. Koellner** revised the manuscript.

I. Kim is the corresponding author

Manuscript 2 (Chapter 3):

Authors : Ilkwon Kim, Sebastian Arnold, Sora Ahn, Quang Bao Le, Seong Joon Kim, Soo Jin Park, and Thomas Koellner

Title : Land use change and ecosystem services in mountainous watershed: Predicting the consequences of environmental policies with cellular automata and hydrological modeling

Journal : *Environmental Modelling and Software*

Status : Under review

Own and author contribution statement :

Own contribution : concept and study design 50%, data acquisition 50%, data analysis and model development, figures 50%, discussion of results 50%, manuscript writing 50%

I. Kim, S. Arnold, Q. Le, S.J. Kim, S.J. Park and T. Koellner designed the research; **I. Kim, S. Arnhold and S. Ahn** collected research data; **I. Kim, Q. Le, and S. Arhnold** analyzed the data and developed model **I. Kim and S. Arnhold** created figures and tables; **I. Kim, S. Arnhold and T. Koellner** interpreted and discussed results; **I. Kim and S. Arnhold** wrote the first draft of the manuscript; **I. Kim, S. Arnhold and T. Koellner** revised the manuscript.

S. Arhnold is the corresponding author

Manuscript 3 (Chapter 4):

Authors: Ilkwon Kim, Patrick Poppenborg, Soo Jin Park, and Thomas Koellner

Title : Simulation of agricultural land-use changes and ecosystem services in a mountainous agricultural region using an agent-based model (ABM)

Status : In preparation for publication

Own contribution : concept and study design 70%, data acquisition 20%, data analysis and model development 80%, figures 100%, discussion of results 80%, manuscript writing 80%

I. Kim, S.J. Park and T. Koellner designed the research; **I. Kim and P. Poppenborg** collected research data; **I. Kim** analyzed the data and develop model; **I.Kim** created figures and tables; **I. Kim, P. Poppenborg and T. Koellner** interpreted and discussed results; **I. Kim** wrote the first draft of the manuscript; **I. Kim, P. Poppenborg and T. Koellner** revised the manuscript.

I. Kim is the corresponding author

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Chapter 2 Driving forces in archetypical land-use changes in a mountainous watershed in East Asia

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Abstract

Identifying patterns and drivers of regional land use changes is crucial for supporting land management and planning. Doing so for mountain ecosystems in East Asia, such as the So-yang River Basin in South Korea, has until now been a challenge because of extreme social and ecological complexities. Applying the techniques of geographic information systems (GIS) and statistical modeling via multinomial logistic regression (MNL), we attempted to examine various hypothesized drivers of land use changes, over the period 1980 to 2000. The hypothesized drivers included variables of topography, accessibility, spatial zoning policies and neighboring land use. Before the inferential statistical analyses, we identified the optimal neighborhood extents for each land use type. The two archetypical sub-periods, *i.e.*, 1980–1990 with agricultural expansions and 1990–2000 with reforestation, have similar causal drivers, such as topographic factors, which are related to characteristics of mountainous areas, neighborhood land use, and spatial zoning policies, of land use changes. Since the statistical models robustly capture the mutual effects of biophysical heterogeneity, neighborhood characteristics and spatial zoning regulation on long-term land use changes, they are valuable for developing coupled models of social-ecological systems to simulate land use and dependent ecosystem services, and to support sustainable land management.

Keywords: land-use change, driving factors, So-yang River Basin, multinomial logistic regression (MNL), heterogeneity, neighborhood effect

2.1 Introduction

Land use and land cover change (LUCC) is regarded as one of the prime determining factors of global environmental change, with significant impacts on ecosystems, climate and human vulnerability (Foley et al., 2005; Verburg et al., 2011). Human impacts on ecosystems mainly occur via land-cover conversion, land degradation or land-use intensification (Lambin et al., 2003). The impacts of LUCC are probably most serious in mountain regions, which are centers of global biodiversity and provide essential services for at least half of the global population (Körner and Ohsawa, 2005). Despite the fact that mountain ecosystems are changing rapidly in response to diverse natural and anthropogenic drivers and are characterized by high social-ecological heterogeneity, so far LUCC studies have not been as focused on mountain regions when compared to other areas for LUCC process (Körner and Ohsawa, 2005). Many LUCC researches for mountain regions focused on the land abandonment in upland areas, though other phenomena are also important LUCC processes in mountainous areas (Monteiro et al., 2011).

In land-use studies, the main goals include finding the biophysical and human drivers of land-use and land-cover change, and understanding how they affect the structure and function of terrestrial systems (Rindfuss et al., 2004). Drivers of LUCC are defined as proximate and underlying factors (Geist and Lambin, 2002). Underlying driving factors such as the systemic and structural conditions of human-environmental relations, reflecting accessibility to land, labor, capital, technology and information, lead to proximate causes (human activities and immediate actions) of LUCC at specific levels (Lambin et al., 2003). However, the make-up of driving factors for LUCC differs across specific regions (Kasperson et al., 1996; Schneider and Pontius, 2001). Moreover, the same driving factors may generate different LUCC patterns in different locations. Studies on LUCC therefore need to account for spatial characteristics at the landscape scale (Verburg et al., 2010). Consequently, one pertinent research question is how various driving forces and actors cumulatively affect LUCC in a given spatial context.

Models of LUCC could represent various aspects of complexity of land-use systems. These models analyze the causes and consequences of LUCC to better understand the functioning of the land use system, thereby supporting land use planning and policies (Verburg et al., 2004c; Anselme et al., 2010, Perez-Vega et al., 2012). These models make it possible to understand LUCC by using selected variables, while trying to predict both the location and magnitude of changes (Veldkamp and Lambin, 2001). In particular, descriptive LUCC models, based on spatially explicit influential statistics using regression analysis, explain relations between LUCC and driving factors to understand underlying causalities assuming existing theories and hypotheses (Schneider and Pontius, 2001). Multinomial logistic regression (MNL) analysis is a widely used statistical approach to identify significant causal factors of LUCC with various types of independent variables reflecting socio-economic and environmental factors (Rutherford et al., 2007; Müller and Zeller, 2002; Monroe et al., 2004). Once validated empirical statistical models can predict future LUCC patterns in response to different changing scenarios of selected driving factors, these models are helpful for informing land use planning practice and policy (Veldkamp and Lambin, 2001; Serneels and Lambin, 2001; Washington et al., 2010).

Given the high social-ecological heterogeneity and diverse natural-anthropogenic drivers of changes in mountain ecosystems (Körner and Ohsawa, 2005), a comprehensive understanding of the potential drivers of LUCC is currently lacking in existing studies of mountainous areas. While much research focuses on specific land-use transitions such as urbanization, urban sprawl, or (de)forestation, analyses of multi-directional land-use conversions are comparably rare, despite their importance for guiding integrated regional planning. In a heterogeneous mountain environment, spatial interactions, such as the effects of neighborhood land-use patterns on LUCC at particular locations, are important drivers (Verburg et al., 2004a). To our knowledge no LUCC studies in Asia-Pacific mountainous areas have considered these spatial interactive effects. So far there have been only a few LUCC studies in the European Alps that have considered neighborhood effects (e.g., Rutherford et al. (2007)). However, these studies are still limited to the assumption of a fixed neighborhood extent (i.e., 5 × 5 pixels) given that the optimal extent may vary according to land-use types and regional conditions (Verburg et al., 2004a; Verburg et al., 2004b).

So far, research on LUCC in South Korea has focused on spatio-temporal patterns and causal factors of urban expansion, in part due to rapid urbanization since the 1960's. Mountainous areas, which cover over

60% of the country, were excluded from these studies, with the exception of some forest cover change research. These studies were conducted with the aim of identifying the probable causes of LUCC using logistic regression analysis (Kim, 2002; Kim et al., 2007b), or to predict future LUCC based on existing prediction models that were built on the identified causation patterns of urban areas (Kim et al., 2007a; Lee et al., 2011). Land-use studies in rural areas mainly focused on patterns of spatio-temporal changes to understand urbanization processes at rural scales (Hwang and Ko, 2007; Ji and Yeo, 2007; Gao and Kim, 2011). However, LUCC in rural mountainous areas are significant and relevant issues in South Korea, leading to significant effects on ecosystem functioning through, e.g., soil and water pollution by chemical fertilizers (Kim et al., 2001). Rural mountainous areas have experienced spatially concentrated LUCC and forest transitions due to various driving forces such as regional policies, population migration and changes in rural industrial structures (Bae et al., 2012). Moreover, mountainous areas in East Asia have experienced reforestation phenomenon based on governmental planning and zoning policies since the 1970's (Bae et al., 2012; Fang et al., 2001). Although these policies were helpful in maintaining forest resources, there were some environmental problems from intensive agricultural activities in these regions. Currently, although understanding of LUCC processes in agricultural mountainous areas in East Asia are necessary to solve environmental problems based on human-induced land-use, such issues are often poorly covered or missing in land-use studies.

This paper aims to quantify spatio-temporal patterns of LUCC and their driving factors in a mountainous watershed of South Korea during archetypical periods of land transition (in sensu Foley et al., 2005). The period 1980–1990 is characterized by agricultural expansion, deforestation and moderate urbanization. In contrast the period 1990–2000 shows an agricultural contraction, reforestation but severe urbanization. These two periods represent typical land transitions of the region along an economic development path. To fill the gaps in current understanding of such LUCC in mountainous areas, we examined the effects of neighborhood land-use and environmental factors on LUCC along with a wide range of other socio-ecological explanatory factors. The general aim is to support regional land-use planning policy and practice, as well as the development of integrated LUCC in the case study region or other similar areas.

2.2 Method

2.2.1 Study area

The So-yang River is located in the north-eastern part of the Gangwon province, near the border between South and North Korea (Figure 2.1). This river is a major tributary of the Han River which originates in North Korea and flows across from North Korea to Chun-cheon in South Korea. The river is regarded as an important source of drinking water for the Seoul metropolitan area and as an important military site near the border of North Korea.

It is difficult to utilize land resources in an efficient way due to geographical characteristics of the region as it is also strongly regulated for environmental (water regulation) and security reasons. Forests, which cover 90% of the land area in the region, although mainly publicly owned, have been excluded from regional development plans. Due to natural (mountainous topographic) and social (regulation policies) constraints, land-uses activities have focused on riverside areas where there are more opportunities to develop agricultural and industrial facilities than forest areas with overlapping land regulations (Kim, 2006). These limitations on regional development made people immigrate to other urban areas, to find income sources and jobs, and eventually have withered regional economies (Kim, 2006). Moreover, dam construction in the So-yang River worsened agricultural conditions, with local climate changes and accessibilities to infrastructures adding further to the difficulties (Choi, 2001). Population in the region decreased following the dam's construction and urban migration trend in South Korea since 1960's, this has generated fragmented land use, such as abandoned houses and farm areas (Yoon, 2010). While population and residential areas have decreased in rural upstream counties, there has been urbanization of residential areas and increased sprawl of tourism facilities downstream in Chun-cheon city (Yoon, 2010). Highland farming has expanded since the 1970's to produce commercial crops in agricultural areas and has become a major income source for farm households (Choi, 2001). One of the most serious environmental problems related to LUCC by human activities arose in the summer of 2006. During that summer, typhoons and heavy downpours of rain lead to a significant decrease in water quality by siltation and water pollutants from agricultural land. Highland agriculture, where soil is reconditioned to retain soil fertility, is considered as a major source of soil erosion, soil degradation and water pollution (Lee, 2008; Thanh Nguyen et al., 2012). In recent years, regional governments have tried to foster organic management of fields, wary of soil and water pollution caused by highland-farming. They offered incentives to people that returned to organic farming (Hoang and Thanh Nguyen, 2013). By efforts to improve housing and recreational facilities in the area, some towns have recently experienced population growth (Yoon, 2010). In this situation, it is necessary to understand the characteristics of underlying LUCC and to identify solutions for future environmental and land-use plans.

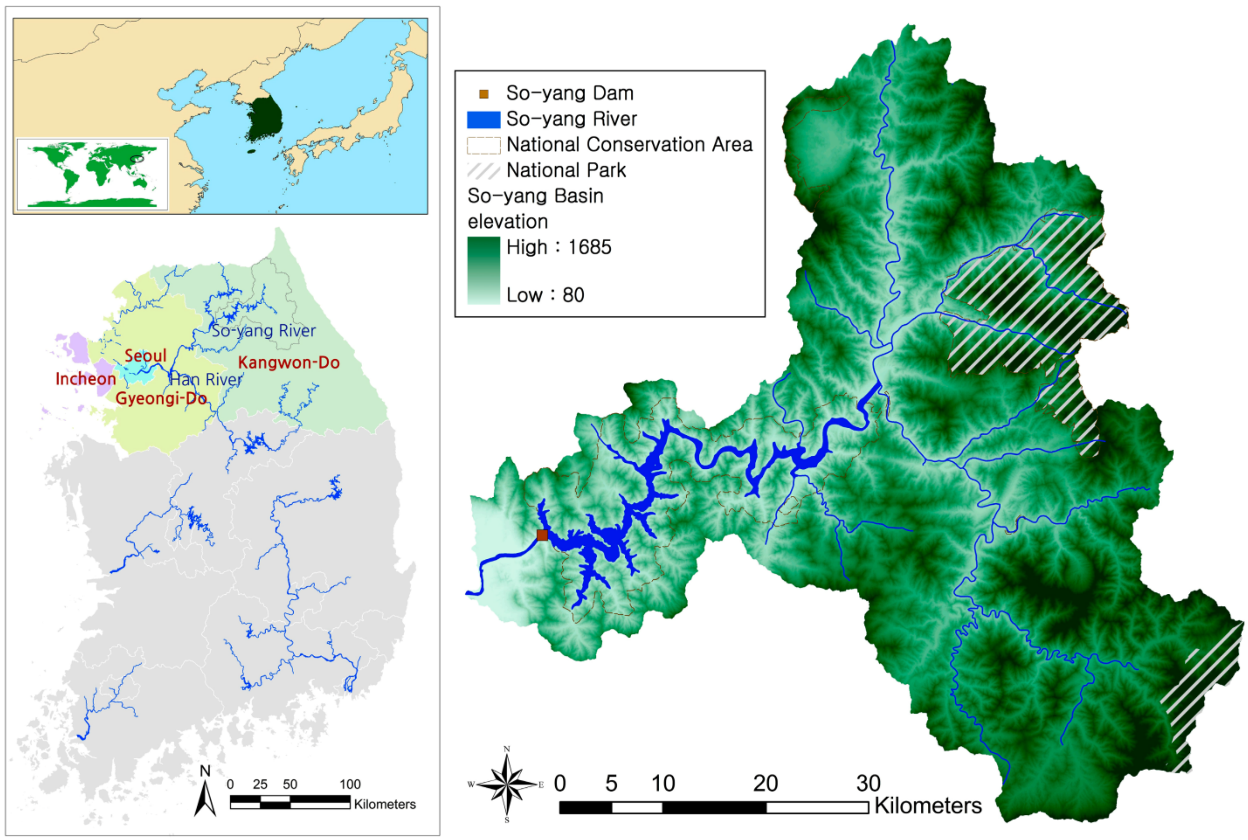

Figure 2. 1 So-yang River Basin in South Korea, Study area (128°19′22″~128°12′11″ N, 37°53′53″~37°58′50″ E).

2.2.2 Multinomial logistic regression modeling of land-use changes

MNL is an extended form of binary logistic regression used widely in LUCC studies (Rutherford et al., 2007; Müller and Zeller, 2002). MNL allows multiple categories as dependent variables that reflect land-use types, while independent variables that reflect LUCC determinants are normally continuous variables (Lesschen et al., 2005). The results from parameter estimation indicate probabilities of change for specific land-use types related to a reference category of unchanged areas, the sum of probabilities for each LUCC are 1 (Overmas et al., 2007). MNL models estimate the direction and intensity of the dependent variables used as explanatory variables by predicting a probability outcome associated with each category of the dependent variable. The probability that Y = h can be stated as:

$$P(Y = h) = \frac{e^{\beta' \chi_{lh}}}{\sum_{m=1}^{M} e^{\beta' \chi_{lm}}} \tag{2.1}$$

where m denotes the LC classes used for analysis, β is a vector of estimation parameters and x_l are the exogenous variables for all Y and at all locations *l*. This equation holds, if the error terms are independently and identically distributed as log Weibull (Lesschen et al., 2005; McFadden, 1973). Normalizing all probabilities yields a log-odds ratio (Lesschen et al., 2005; Greene, 2012):

$$\ln \left[\frac{P_{lh}}{P_{lm}}\right] = x'_l(\beta_h - \beta_m) \tag{2.2}$$

The dependent variable is expressed as the log of the odds of one alternative, relative to a base alternative. If model assumptions hold, the maximum likelihood estimators are asymptotically normally distributed, with a mean of zero and a variance of one for large samples. The significance of estimators is tested with z-statistics, which are reported in the output tables. Likelihood-ratio (LR) tests compare the log likelihood from the full model with that of a reduced model omitting explanatory variables. To test the hypothesis with (m-1) parameters, a likelihood-ratio and Wald test can be used (Müller and Zeller, 2002).

We used MNL models of multi-directional conversions of urban, forest and agricultural types during the periods of 1980-1990 and 1990-2000 to determine patterns and factors of LUCC phenomena reflecting human-environmental interactions (Figure 2.2). Urbanizations and agricultural expansions are typical examples of human-driven LUCC that have altered the landscape and ecosystems drastically (Guerschman et al., 2003). Forest change is also regarded as a significant LUCC process because it is the dominant cover type in the region and central to the artificial LUCC in the marginal areas.

Validations of models are evaluated using the area under relative operating characteristics (ROC). The area under the ROC curve (AUC) is an index of discrimination accuracy that can validate possibilities of LUCC independent of any specified quantity of LUCC. The index is 1 when the model has perfect assignments to probability of LUCC. If ROC is 0.5 the model has random probability. If the index is higher than 0.5 the model performs better than chance (Pontius and Schnieder, 2001; Temme and Verburg, 2011).

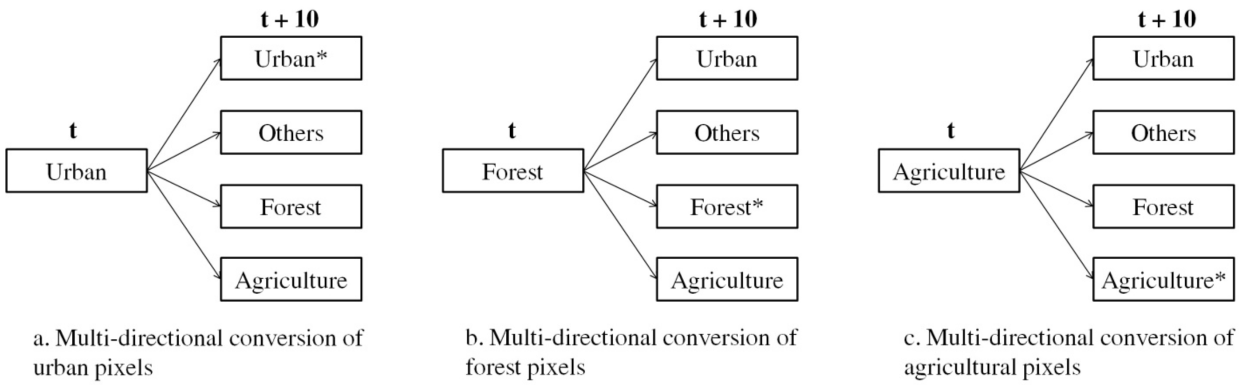

Figure 2. 2 Three types of multi-directional conversions for three corresponding multinomial logistic regression (MNL) models (Note: Each model will be considered in two periods: 1980–1990 and 1990–2000. (Category with * is used as reference category reflecting unchanged land).

2.2.3 Explanatory factors, their causal hypotheses and data sources

Land-use maps of 1980 produced from Landsat MSS with a 60 m × 60 m resolution and 1990 and 2000 produced from Landsat TM satellite imagery with a 30 m × 30 m resolution are obtained from the website of the Korean Water Management Information System (WAMIS, 2012). To determine patterns and factors of LUCC, urban, forest and agriculture land-cover types are selected in this research. Pixels that are classified as water are excluded prior to LUCC analyses to simplify extraction of correct land-use types. Variables on LUCC are diverse and often selected differently according to their expected effect on LUCC (Corbello-Rico et al., 2012). Environmental variables are mapped at a resolution of 90 m and produced by DIGEM 2.0 software (Conrad, 1998). Rainfall data are interpolated from weather stations data using an Inverted Distance Weight (IDW) method. Distance variables are calculated based on digital base maps, all done by ArcGIS 9.3's spatial analyst tool. In this research, the environment, distance, neighborhood and population variables reflecting various characteristics of the region are hypothesized as explanatory factors of LUCC.

Rainfall is selected as an expected climate LUCC factor, because rainfall fluctuation and amounts generate changes in crop yields and land-use practices (Veldkamp and Fresco, 1996). In this research, we used summer rainfall, because rainfall is centered in the summer monsoon and typhoons, generating significant flood damage to agricultural and urban areas. Among independent variables, geomorphologic factors reflecting topographic conditions are important for determining LUCC. Elevation is regarded as a significant LUCC factor, as while lower elevation areas along rivers are generally more suitable for human settlements and agricultural activities than higher areas (Hall et al., 1995). Slope is important for determining factors of LUCC especially in mountainous areas, because residential areas are characterized by lowest slope and agricultural lands are organized around the residential areas with gentle slopes (Mottet et al., 2006). Upslope contributing area, reflecting runoff and flow of water, is selected as a factor representing potential and risk of agricultural production (Le et al., 2008). Wetness index is also an important variable and represents temporary spatial flow of water bodies in the event of rain. It is selected to determine hydrological influences on LUCC and interactions between hydrology, soil, climate, and land-use (Blanchard and Lerch, 2000). Distance to urban areas, roads, and streams as natural and artificial LUCC factors are set as LUCC factors because anthropogenic land-uses largely take place near roads and existing urban areas (Millington et al., 2007), as well as near river systems. Interactions between neighboring land-use types are major LUCC factors in many land-use models which influence decision-making processes of land-users and land-use policies. As patterns of LUCC have self-organizing characteristics, such as urbanization, neighborhood interactions are considered as major factors of LUCC (Verburg et al., 2004a). Moreover, phenomena of LUCC such as urbanization, forestation and agricultural expansion are likely to occur in boundary areas. For these reasons, enrichment factors (EF) to reflect neighborhood interactions are selected as expected driving factors. Human population is also a significant driving factor of LUCC. Urbanization and agricultural expansion are driven by population growth, while population changes affect regional socio-political and economic conditions (Meyer and Turner, 1992). Land regulation policies as a form of land zoning are significant LUCC factors, causing land use and environmental changes such as mitigation of deforestation (Dewi et al., 2013). In the So-yang River Basin, there exist many overlapping zoning policies to protect mountain and water sources (Kim, 2006). We selected two zoning policies, one is a national conservation area, which was set to protect water sources and mountainous ecosystems and the other is a national park which was established to manage mountain resources under strong regulation. These two zoning policies are merged into one regulation variable as a categorical variable in our model, where a value of 1 is natural conservation areas designated in 1975 and value of 2 is Sol-ak National Park designated in 1970, which means stronger land regulation to protect forest resources. These expected driving factors are hypothesized as expected determinants of LUCC (Table 2.1).

Table 2. 1 Selected explanatory variables, their hypothesized effects, and data sources.

Variables	Abbreviation	Hypothesized effect on conversion to			Data Source
		Urban	Forest	Agri	
Biophysical					
Summer rainfall (mm)	S_RAIN	—	+	—	WAMIS[1]
Altitude (m)	ALT	—	+	—	Aster GDEM
Slope (°)	SLO	—	+	—	Conrad (1998)
Upslope contributing area (m^2/m)	UPS	—	+	—	Conrad (1998)
Wetness index (= in (UPS/tan(SLO)))	WET	—	+	—	Conrad (1998)
Distance					
Distance to road (m)	D_ROAD	—	+	—	ITS[2]
Distance to stream network (m)	D_STR	—	+	—	WAMIS
Distance to urban area (m)	D_URBAN	—	+	—	WAMIS land-use maps
Neighboring land-use[3]					
Enrichment factors of urban	EF_URBAN*i*[4]	+	—	—	LUCC maps
Enrichment factors of others	EF_OTHER*i*	+	—	+	LUCC maps
Enrichment factors of forest	EF_FOREST*i*	—	+	—	LUCC maps
Enrichment factors of agriculture	EF_AGRI*i*	—	—	+	LUCC maps
Land regulation policy					
Regulation Zone	REG[5]	—	+	—	WAMIS
Population					
Population density (people/km^2)	P_DENS	+	—	+	Statistical data

1. WAMIS (Water Management Information System) in South Korea

2. ITS (Intelligent Traffic System) in South Korea

3. see section 2.4 for detailed explanation

4. where *i* = optimal neighborhood size of each land-use type (see section 2.4 for detailed calculation procedure)

5.REG=0 is no protection mode applied as a redundant variable, REG=1 is natural conservation code applied from 1971, REG=2 is national park code applied from 1970

2.2.4 Neighborhood interactions of land-use

Neighborhood relationships to land-uses are regarded as important LUCC factors. Neighborhood relations are spatial interactions with adjacent areas who's influence diminishes with distance (Barredo et al., 2003; Geertman et al., 2007). To analyze and quantify neighborhood characteristics of LUCC, we used the concepts and methods of land-use EFs, as proposed by Verburg et al. (2004b). The EFs refer to the abundance of a land-use type in the neighborhood of a specific raster cell, determined by the occurrence of the specific land-use type in the entire area (Verburg et al., 2004b; Hallin-Pihlatie, 2009; Pan et al., 2010). The equation for EFs is as follows:

$$F_{i,k,d} = \frac{n_{k,d,i}/n_{d,i}}{N_k/N} \tag{2.3}$$

where $F_{i,k,d}$ characterizes the enrichment of neighborhood d at location i with land-use type k. The shape and distance of the neighborhood from the central cell i is identified by neighborhood d (Figure 2.3). The result for each cell i means enrichments factors for the different land-use types k. This calculation is repeated for varying neighborhood sizes at different distances d. After this calculation, the average neighborhood characteristic for a specific land-use type l is calculated by extracting the average of the EFs for all grid cells into a certain land use type l.

$$\bar{F}_{i,k,d} = \frac{1}{N}\sum_{i\in L} F_{i,k,d} \tag{2.4}$$

where L is the set of all locations with land-use type l and N_l, the total number of grid cells within this set. In this study, we used ArcGIS based calculations of EFs as done by Hallin-Pihlatie (2009). The EFs are presented on logarithmic scales to obtain equal scales for land-use types that occur more than average in the neighborhood (EF > 1) and less than average in the neighborhood (EF < 1). When the values are close to 0, there are no neighborhood effects for land-use and land cells are randomly distributed compositions of a random selection of grid-cells regardless of neighborhood effects. After calculating neighborhood EFs, optimal neighborhood extent to give highest level of neighborhood explanation is selected for each land-use type (Verburg et al., 2004b). As optimal neighborhood sizes are varied for each land-use type, different neighborhood sizes are considered in this model.

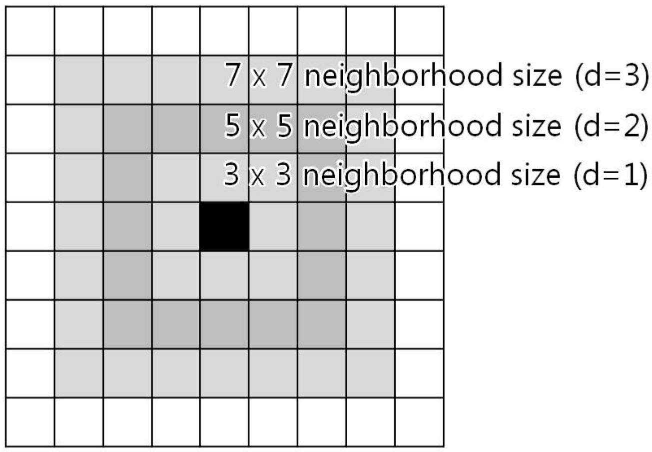

Figure 2. 3 Configuration of neighborhood size (advised from Verburg et al., 2004b).

2.3 Results

2.3.1 Temporal land cover changes between 1980 and 2000

In the first period from 1980 to 1990, the study area experienced growth in urban and agricultural areas as well as loss in forest areas. Although urban classes had low shares in the region, the rate of change in these classes is higher than for other land-use classes. Agricultural land-use increased in this period where forest remained constant as can be seen in (Table 2.2). LUCC patterns between 1990 and 2000 show differences when compared to the earlier period. While urban and forest areas have increased, agricultural land decreased in the later period. These LUCC mainly occurred due to urban expansions in the Chun-cheon area. Forest changed to a small degree under the influence of zoning of national protection areas, which made it difficult to utilize forest resources.

Table 2. 2 Land-use changes between 1980 and 2000.

Land-cover	Area (km^2)			Net Change		80-90 (% of	90-00 (% of
	1980	1990	2000	80-90 (km^2)	90-00 (km^2)	initial area	initial area
Urban	8.16	11.41	19.33	3.25	6.71	39.78	52.87
Forest	2428.68	2411.70	2430.82	-16.97	19.10	-0.70	0.79
Agriculture	108.01	119.81	113.03	11.80	-6.78	10.93	-5.66
Others	18.15	20.08	16.81	1.93	-6.24	10.62	-27.12

2.3.2 Neighborhood factors of land-use changes

To understand interactions of EFs with LUCC, we calculated neighborhood EFs of pixels with land-cover changes in ArcGIS. EFs of changing areas of specific land-use types between 1980 and 1990 are presented in Figure 2.4. Most land-use types with neighborhood factors tend to become less influenced with increasing distance to the central cell. From this result, it was apparent that urban and agricultural LUCC in these regions are related to existing urban areas, while forest expansion is mostly situated near land-use types such as grasslands and bare soil. All considered land-use types show negative correlations with forest EFs, which are reflected in LUCC. These occur less frequently in mountainous areas with forest, and also for forest expansions. These tendencies are also present in the next period between 1990 and 2000. New urban areas are located near the neighboring areas of existing urban lands, while forest and agricultural growths occur in the neighborhood of other land types and urban areas as seen in Figure 2.5. LUCC in this period also appeared in the areas dominated by forest, which have similar EFs of distance and neighboring areas in comparison with the earlier period.

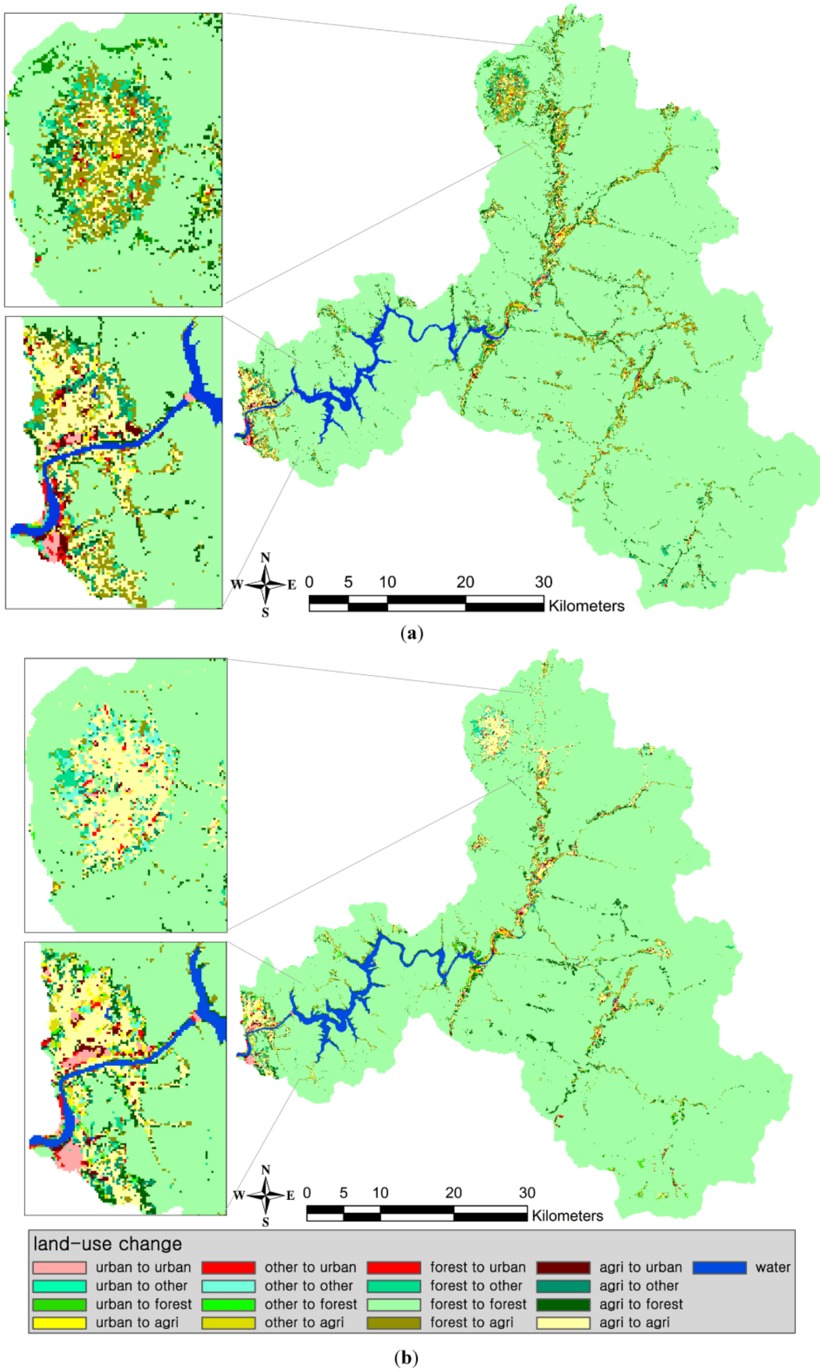

Figure 2. 4 Temporal land-use changes between 1980-1990(a) and 1990-2000(b) in the So-yang River Basin.

Compared to urban and agricultural land-use, new forest areas are more easily affected by the neighboring land-use as seen in Figure 2.5. Hence, EFs of all land-use types to new forest areas reach threshold points with drastic decreases of neighboring EFs. The EFs with the highest values for each land-use are used as boundaries determining neighborhood land-use variables in logistic regression analysis. In many cases, neighborhood relations are visible for the immediate neighbors. With these nearest neighbors, EFs with neighborhood size (7 × 7 grid size) are used in logistic regression to represent influences of neighboring urban lands to new urban and agricultural areas, and the influence of neighboring forest to new agricultural areas in the first decade. In the later period, EFs with neighborhood size (5 × 5 grid size) are added to represent influences of both neighboring forest and agricultural areas to new agricultural areas and neighboring urban areas to new urban areas.

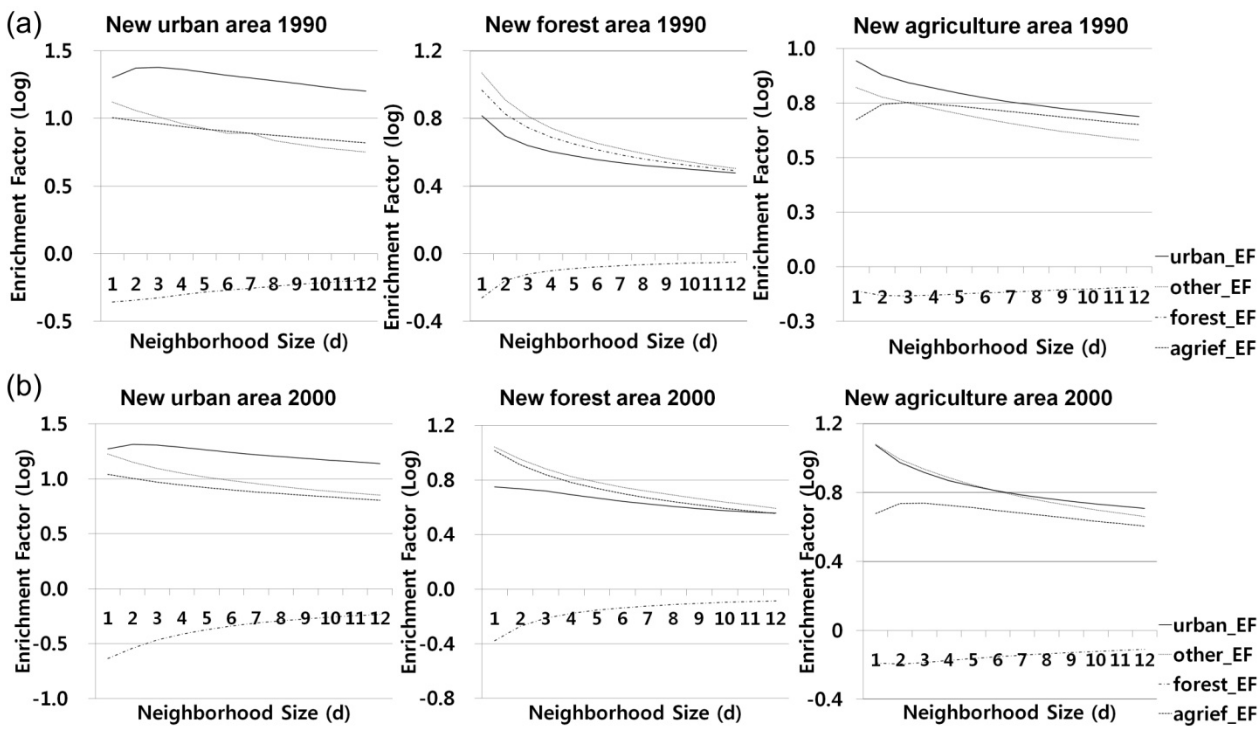

Figure 2. 5 Enrichment factors (EF) of land-use changes between 1980-1990 (a) and 1990-2000 (b)

2.3.2 Land-use change factors from logistic regression

To extract LUCC factors and quantify the influence of explanatory variables, MNL models are applied. The statistical analyses are conducted for all grid cells in the region. The results of logistic models are illustrated for each land-use type in Table 2.3, Table 2.4, Table 2.5, Table 2.6, Table 2.7 and Table 2.8. These models are applied to areas with a high probability of LUCC between two time periods. Odds ratio values indicate changes in odds of LUCC upon changes on independent variables (explanatory variables) (Verburg et al., 2004a). The values between 0 and 1 indicate that an increase in the values of independent variables leads to a decrease in possibility of LUCC. On the contrary to this, values above 1 indicate that an increase in values of independent variables leads to an increase in possibility of LUCC. (Verburg et al., 2004a). In statistical results, environmental and neighborhood variables have higher or lower odds ratio values than distance variables with values around 1. This result could be interpreted as LUCC are more likely influenced by changes on environmental and neighborhood variables. These logistic models have good explanatory ability with high degrees of AUC values with 0.751–977 (see Table 2.3, Table 2.4, Table 2.5, Table 2.6, Table 2.7 and Table 2.8), which mean that LUCC could be explained by independent variables (Schneider and Pontius, 2001; Verburg et al., 2004a). These results make it possible to simulate locations of LUCC areas based on the independent variables used in this study.

Results of urban change models are shown in Table 2.3 and Table 2.4. Major driving factors affecting urban conversion are elevation and neighboring urban areas with significant probabilities. Urban areas with high elevation and small patches are easily converted to other land-use types. In the case of urban LUCC, environmental factors like elevation and slope are less affected by urban changes when compared with other LUCC.

Table 2. 3 Factors of urban land-use changes using logistic regression (1980-1990)

Variable	Urban to others		Urban to forest		Urban to agriculture	
	Coefficient (B)	Odds ratio	Coefficient (B)	Odds ratio	Coefficient (B)	Odds ratio
S_RAIN	.013**	1.013	-.002	.998	-.005	.995
ALT	.010**	1.010	.011**	1.011	.005*	1.005
SLO	.005	1.005	.084**	1.088	.015	1.015
UPS	-.766*	.465	-.364	.695	-.598*	.550
D_RIV	.001*	1.001	.000*	1.000	.001**	1.001
D_STR	.000	1.000	.001	1.001	-.001	.999
P_DENS	.000	1.000	.000	1.000	.000**	1.000
EF_URBAN7	-.019**	.981	-.024**	.976	-.012**	.988
EF_FOREST7	-4.875**	.006	-.401	669	.416	1.515
EF_AGRI7	-.122**	.865	-.155**	.856	-.019	.982
Constant	-6.647		1.162		5.492	
AUC	0.765		0.886		0.790	

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

Table 2. 4 Factors of urban land-use changes using logistic regression (1990-2000)

Variable	Urban to others		Urban to forest		Urban to agriculture	
	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio
S_RAIN	.016*	1.016	.020**	1.009	.006	1.006
ALT	.000	1.000	.003**	1.003	-.001*	.999
SLO	-.094*	.910	.007	1.007	-.058**	.944
D_STR	.002**	1.002	.000	1.000	.001	1.001
D_URBAN	-.009	.991	.016**	1.016	.014**	1.014
P_DENS	-.003*	.997	-.004*	.996	-.002**	.998
EF_URBAN5	-.024**	.977	-.016**	.983	-.014**	.986
EF_FOREST5	-2.974*	..051	3.979**	53.458	1.313**	3.717
EF_AGRI7	-.073	.930	.132**	1.141	.044	.1.045
REG=1	-1.070	.343	1.185**	3.272	.378	1.459
REG=2	.406	1.500	16.804	19859902.0	16.422	13555256.2
REG=0	0		0		0	
Constant	-11.841		-18.684		-3.787	
AUC	0.751		0.901		0.804	

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

Results of LUCC models in relation to forests are shown in Table 2.5 and Table 2.6. Forest LUCC are related to environmental factors and neighboring forest areas. In the case of forest changes, forest neighborhood variables show different correlation directions according to size of forest and neighboring urban areas.

Table 2. 5 Factors of forest land-use changes using logistic regression

Variable	Forest to urban		Forest to others		Forest to agriculture	
	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio
S_RAIN	-.001	.999	.000	1.000	-.009**	.991
ALT	-.001**	.999	.000	1.000	-.003**	.997
SLO	-.150**	.860	-.117**	.890	-.098**	.907
UPS	-.010	.990	.298	1.347	.219**	1.245
D_STR	-.001*	.999	.001	1.001	-.001**	.999

D_URBAN	-.002**	.998	-.001**	.999	-.001**	.999
P_DENS	.000	1.000	.000	1.000	-.001**	.999
EF_FOREST3	1.815*	6.143	2.005**	7.423	.737*	2.089
EF_FOREST7	-6.513**	.001	-6.137**	.002	-3.583**	.028
EF_AGRI7	.036	1.037	.042	1.043	.103**	1.108
REG=1	-1.125	.325	.988*	2.685	-.410**	.664
REG=2	1.936*	6.934	-18.356	1.067E-8	-.856*	.425
REG=0	0		0			
Constant	3.091		.130		7.996	
AUC	0.977		0.953		0.950	

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

Table 2. 6 Factors of forest land-use changes using logistic regression

Variable	Forest to urban		Forest to others		Forest to agriculture	
	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio
ALT	-.002	.998	-.003**	.997	-.005**	.995
SLO	-.093**	.911	-.076**	.927	-.066**	.936
UPS	.061	1.063	.103	1.109	.369**	1.446
D_STR	-.003*	.997	.000	1.000	-.001**	.999
D_ROAD	-.001	.999	.000	1.000	.000**	1.000
D_URBAN	-.003*	.999	.000*	1.000	-.001**	.999
EF_FOREST3	2.981	19.704	4.794**	120.751	-.528	.590
EF_FOREST5	-4.849*	.008	-8.733**	.000	-.457	.633
EF_AGRI7	.086	1.089	-.068*	.934	.162**	1.175
Constant	-.429		1.504		-.330	
AUC	0.951		0.939		0.942	

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

Agricultural land-use models are shown in Table 2.7 and Table 2.8. Agricultural land-use changes have similar environmental driving factors as urban growth. These environmental factors reflecting topographical conditions are less influential to agricultural changes than forest.

Table 2. 7 Factors of agricultural land-use changes using logistic regression (1980-1990)

Variable	Agriculture to urban		Agriculture to others		Agriculture to forest	
	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio
S_RAIN	.001	1.001	.010**	1.009	-.002**	.998
ALT	.001*	1.001	.002**	1.002	.003**	1.003
SLO	-.050**	.951	.013	1.013	.096**	1.100
UPS	.043	1.044	.386**	1.471	.096*	1.101
D_STR	.001**	1.001	.001**	1.001	.000	1.000
P_DENS	.001**	1.001	.001**	1.001	.000	1.000
EF_URBAN7	.014**	1.014	-.006*	.994	-.013**	.987
EF_FOREST3	.156	1.169	-.759**	.468	-.610**	.544
EF_FOREST7	-1.013	.363	-2.091**	.124	.958**	2.606
EF_AGRI7	-.016	.985	-.030	.970	-.085**	.919
REG=1	.793*	2.209	1.535**	4.642	.018	1.018
REG=2	-.713	.490	.300	1.350	.274	1.315
REG=0	0		0		0	
Constant	-2.996		-9.419		-.365	
AUC	0.821		0.778		0.785	

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

Table 2. 8 Factors of agricultural land-use changes using logistic regression (1990-2000)

Variable	Agriculture to urban		Agriculture to others		Agriculture to forest	
	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio	Coefficient (B)	Odds Ratio
S_RAIN	-.001	.999	.017**	1.017	.015**	1.015
ALT	.000	1.000	-.003**	.997	.002**	1.002
SLO	-.020**	.980	.022**	1.022	.052**	1.054
D_STR	.000	1.000	.001**	1.001	.000**	1.000
D_URBAN	-.003**	.997	.000	1.000	.001**	1.001
P_DENS	.000**	1.000	.000	1.000	-.001**	.999
EF_URBAN5	.021**	1.022	-.013**	.987	-.002	.998
EF_OTHER5	.014**	1.014	-.002	.998	.008**	1.008
EF_FOREST5	-.363	.695	-2.386**	.092	1.851**	6.368
EF_AGRI3	.019	1.019	-.039*	.962	.061**	1.063
EF_AGRI7	-.027	.974	-.131**	.877	-.071**	.932
REG=1	-.062	.940	.382**	1.465	.478**	1.612
REG=2	-247	1.280	.904	2.469	.380	1.463

REG=0	0		
Constant	-1.126	-13.526	-14.193
AUC	0.798	0.785	0.781

*Significant at $p < 0.05$, **Significant at $p < 0.01$.

2.4 Discussion

2.4.1 Driving factors of land-use changes

In this study, we identified LUCC patterns in the region, which could be compared with archetypical periods of land transition. After that, we extracted variables, which were used as independent variables in multinomial logistic models to analyze LUCC in the So-yang River Basin. Our statistical analysis suggests that LUCC factors and EFs show different patterns for the two different time decades, where the degree of some results of the relations of correlation coefficients and directions of effects vary. Although most results correspond with the research hypothesis of factors of LUCC, some results were unexpected.

2.4.1.1 Driving factors of land-use changes between 1980-1990

Biophysical drivers: The first decade was characterized by agricultural expansions, deforestation and urbanization. During the period after a highway to Seoul was constructed in 1975, commercial highland agriculture increased in the Gangwon province, because it was regarded as a new economic income source in rural mountainous areas (Lee, 1990). During this period, the impacts of environmental factors like summer rainfall, elevation and slope are in accordance with our hypotheses. We hypothesized that summer rainfall has negative explanatory power in relation to urban and agricultural land-use. This is due to the environmental characteristics of the research site, as people in this region have experienced flood damage frequently due to monsoon periods and typhoons. From the analysis, we could find that agricultural areas are easily changed into other land type areas with lower summer rainfall. Topographic factors, specifically elevation and slope have negative correlations to human induced LUCC, as expected. Areas with low elevations and gentle slopes are easily converted to agricultural and urban areas, while forest expansions occurred in areas with low accessibility due to topographic limitations. This result is in concurrence with other studies on agricultural abandonment of mountainous areas in Europe (McDonald et al., 2000) and Asia

(Pingali, 1997). As for upslope contributing areas and wetness index reflecting hydrological and geomorphologic aspects, areas with low upslope contributing area index were converted to agricultural land in the first time period, which does not coincide with our research hypothesis. This result could be explained with rainfall characteristics in the region. Areas with less rainfall intensity during monsoon periods are preferred for new agricultural areas, reflecting the importance of water inflows at upper slopes.

Distance factors and population density: Distance factors and population density have low explanatory powers compared to other variables. This result can be attributed to the fact that LUCC occur in the narrow basin area of the river, which make it difficult to clarify distance effects. Previous research on forest transition in South Korea concluded that the population factor is one of the major LUCC factors in mountainous areas (Bae et al., 2012). However, population density shows insignificant explanatory power to explain LUCC from our statistical analysis.

Neighboring land use: Forest areas highly were correlated with neighboring forest factors, especially neighborhood factors of 7 × 7 grid cells. This suggests that LUCC in the region resulted from spatial policies to restrain urban and agricultural changes near forest areas for security and environmental reasons. Agricultural land in areas dominated by forest is easily converted to forests, which might in addition reflect natural conversions of abandoned fields. However, areas nearest to forest also experienced LUCC to both urban and agricultural lands. These LUCC led to highland agriculture occurring in the marginal forest areas. These results show that factors that affect LUCC differ for each land-use class due to their spatial relations. However, differences between the causal patterns of LUCC in the two periods (1980–1990 and 1990–2000) are relatively low, with the exception of changes of agricultural land-use, meaning that similar driving factors and mechanisms affect LUCC constantly.

Land regulation policies: Land regulation policies during this phase did not affect urban LUCC because there already were a few urban areas located in regulation areas. Sol-ak National Park was designated within the Tae-baek mountain range and had been managed strictly since then because it is one of the most famous national parks and sightseeing areas in South Korea. The national park did not affect LUCC directly after 1980's. However, forest changes next to urban areas in the 1980's could be interpreted by the way that tourism facilities in the park areas were increased more than other urban land use types in this period. Comparing national parks and national conservation areas, the latter are more influential with respect to agricultural LUCC. Since national conservation areas are designated to protect water quality in So-yang Lake, farmlands and farmers were directly affected by this policy and this led to agricultural contraction.

2.4.1.2 Driving factors of land-use changes between 1990-2000

Most LUCC factors hypothesized in this research have consistent explanatory powers between the two different time periods. Although similar factors affect to LUCC steadily, there are some differences of LUCC patterns between earlier and later stemming from the decrease of agricultural areas in the second phase. During this period, agriculture decreased all over the catchment except centralized highland agriculture areas such as Haean Myeon and Jawoon Ri. This change also generated different results in statistical analysis of LUCC factors.

Biophysical drivers: The explanatory power of rainfall is opposite for forest and agricultural LUCC. Agricultural areas with higher summer rainfall are easily converted to forest areas because of problems derived from an increase of summer rainfall (Kim and Lee, 2011), which could generate planned forestation in the agricultural areas to prevent flood damages in the region. In the earlier period, topographic variables of elevation and slope explain urban and agricultural expansions. However, these tendencies have changed in the subsequent period from 1990 to 2000 indicated by influences of slope factors on agricultural lands. In the later period, areas with gentle slope were more easily converted to agricultural lands. This result reflects expansions of highland farming into smooth mountainous areas. In contrast to urban and agricultural expansions, forest expansion occurs at higher elevations and with increased slope, typically abandoned lands with limited use, especially those within national conservation areas. Due to the land regulations at these sites, forest growth occurred in the processes of natural conversion. This difference stems from geomorphologic characteristics of mountainous areas.

Distance factors, population density, and neighborhood land-use: These factors are similar to their results of MNL analysis when compared with the earlier period of 1980-1990. Distance and population factors are still less affected LUCC. Neighborhood factors in the later period affect LUCC similarly to those of the earlier period.

Land regulation policies: Land-use in urban areas affected by land regulation in the later period, barely changes for the entire period.

2.4.2 Underlying factors of land-use changes in the So-yang River Basin

We tried to find driving factors of LUCC. However, LUCC are affected by various factors because of the complex characteristics of human-environmental systems, which are difficult to derive from statistical results. In this chapter, we described underlying factors from literature reviews and briefly compare them with the statistical results which are suggested as major LUCC factors in the local communities.

With respect to urban areas, deregulation in green belt areas to ease local development and improve accessibility by constructing roads and bridges are important LUCC factors (Lee, 2009). In particular, policy changes in 1994 to utilize lands surrounding water sources generated expansions of urban areas in the marginal forest (Choi et al., 1998). However, results of statistical analysis with distance and neighboring factors could not support these findings.

Land abandonment with population migration after zoning policies and dam constructions since 1970's generated growth of natural forest. So-yang Lake generates local climates changes, such as increased days with fog and frost, which worsen agricultural conditions and productivity as well as residential health status (Choi, 2001; Lee, 1990). Moreover, dam constructions brought about a raise of agricultural and living costs by worsening accessibility, and while zoning policies made it more difficult to utilize lands efficiently and get higher income (Choi, 2001; Kim, 2006). These underlying factors could be linked with the results for topographic variables.

Although overall agricultural areas decreased during the period, agricultural expansions occurred in highland farming areas influenced by socio-economic factors such as income improvement in highland crops and support policies for agriculture, which expand cultivation areas of household and reclamation of forest areas (Choi et al., 1998). Apart from this reason, political factors affected agricultural LUCC. Korean agricultural households and societies faced economic crisis after the launch of WTO systems in 1995. To solve this problem, the central government tried to introduce various policies to maintain agricultural sectors, such as farm subsidies and deregulations in agricultural land uses. The Korean government introduced a direct payment system for aged farmers' early retirement and environmentally friendly farming practice since the late 1990's to preserve the income of rural households and promote environmentally friendly farming as a new income source (Im and Lee, 2007). Regulation policies, such as maximum holdings of farmland and lands to the tillers principle regulating landholdings of no-till farmers, were regarded as troublesome factors for agricultural activities in agricultural areas. After the government eased these regulations, land owners could easily increase their land extent with advanced technologies. Aside from these political factors, recent climate changes brought about agro-environmental changes such as temperature rise, intensive rainfall in summer monsoon periods, reduced sunshine hours and fruit cultivation areas advancing north, in the Tae-back mountain range as well as other high elevation areas (Kim and Lee, 2011).

2.4.3 Limitations and the way forward

The challenge of this study is related to acquisition of spatial data for LUCC, population data for driving factors and land use regulation maps for the research site. Land use maps used in the research were produced by an institution of the Korean government as explained in the earlier chapter. Although they had higher reliability compared to other maps, these also had problems with accuracy of classification because they were produced based on different Landsat satellite images. Maps of 1980 were built on Landsat MSS with 60 m resolution, however other maps of 1990 and 2000 were based on Landsat TM with 30 m resolution. This resolution differences may reduce accuracies of "trace" LUCC (i.e., the LUCC areas with only a few 30 m × 30 m pixels. As these differences could affect data accuracy, we used these data by merging pixel resolution, thereby reducing this problem.

Data acquisition significantly affects the accuracy of the land use model (Verburg et al., 2004c). In our study, it was especially problematic to get socio-economic data for detailed administrative areas and to convert these data into spatial data. Although some policy factors like zoning area have spatial dimensions for policy implementations, such low spatial differences of this variable within the study area weakened the measurement of its effect on LUCC when using the spatial statistical models. Moreover, many underlying LUCC factors, such as expansions of highland farming, are difficult to find from this quantitative approach due to data limitations. The same limitation might extend to population density as the population data obtained was based on administrative areas, which means all areas or cells in an administration unit have the same numbers. The weak or null effects of these less spatially distributed variables do not necessarily mean lower importance of these variables in reality (Bae et al., 2012).

The problems of these socio-economic drivers could be moderated through some actor-based follow-up studies reflecting land use decisions. To do so, we could use household surveys to acquire socio-economic data and develop decision models for land use actors. Otherwise, it is necessary to develop methods for spatial disaggregation of statistical data in mountainous regions.

2.5 Conclusions

In this study, we aimed to find LUCC patterns and factors using MNL methods to develop statistical models of LUCC. We extracted neighborhood variables as an index of EFs and various environmental data used as independent variables in multinomial logistic models. After calculating these factors, we quantified relationships between LUCC and their driving factors to urban, forest, and agricultural lands in the So-yang River Basin using three types of MNL. From this statistical analysis, it was concluded that driving factors and EFs showed similar patterns for two different time periods, meaning that similar processes affect LUCC constantly in Asian mountainous watershed areas. Statistical results indicate that topographic and neighborhood factors are major driving factors in urban, forest and agricultural LUCC, corresponding with most hypothesized effects on LUCC. Although major LUCC factors consistently affect all LUCC, these specific models could help to understand spatial determinants of LUCC processes. It turned out that LUCC models should be subdivided into specific land-use types to utilize driving factors of different land-use types. Driving factors reflecting spatial relations could define transition rules in the LUCC models. In particular, simulation models for future LUCC could be developed based on the results of our research. When we compared two models for different time periods, there were some similarities among LUCC factors. On the other side, they represent two archetypical situations. In the earlier period, agricultural expansion, deforestation and moderate urbanization were dominating, while the later was characterized by agricultural contraction, reforestation and severe urbanization. These factors can be used in simulation models (e.g. cellular automata (CA) models) for LUCC changes by quantifying transitional rules and land conversion probabilities of LUCC for specific pixels (e.g. ES models), and by setting neighborhood thresholds for neighborhood interactions. Moreover, we described various underlying factors which are difficult to be found in statistical results, but are relevant for constructing socio-economic and policy scenarios. These land-use simulation models potentially could contribute to enhance policy making with land-use plans and regional environmental management.

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Chapter 3 Land use change and ecosystem services in mountainous watersheds: Predicting the consequences of environmental policies with cellular automata and hydrological modeling

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Abstract

Land use and cover change (LUCC) altered the capacity of mountain watersheds to provide ecosystem services (ES) for downstream water users. Policies aiming at the conservation of ES sometimes fail due to a lack of understanding of the complex dynamics of LUCC and its ecological consequences. We present a modeling framework that predicts both LUCC and ES through a combination of cellular automata (CA) and the Soil and Water Assessment Tool (SWAT). We employed this framework to assess the efficiency of alternative policy instruments including direct payments and command-and-control regulations. The framework successfully captures spatial patterns of LUCC, hydrological processes, and the associated gains and losses in ES. Our results reveal that the performance of policy instruments is highly site-specific and scale-dependent, which may lead to negative externalities ("leakage" effects). Integrated LUCC-ES modeling provides valuable information to assess the efficiency and targeting of proposed policies to achieve future conservation goals.

Keywords: Direct payments, Fresh water supply, NetLogo, Regulation, Soil and Water Assessment Tool (SWAT).

3.1 Introduction

Mountainous watersheds provide a wide range of essential ecosystem services (ES) to human society, most notably through the supply of purified fresh water from upstream headwater catchments (MA, 2005; TEEB, 2012). Land use and cover change (LUCC), however, has altered the capacity of these natural "water towers" to regulate the hydrologic cycle and to control downstream water quantity and quality (Allen, 2004; Bhaduri et al., 2000). Deforestation and clearance of natural vegetation through agricultural expansion has increased the supply of provisioning ES such as food, fiber, and bioenergy (Power, 2010; Zhang et al., 2007), but has caused dramatic environmental degradation through losses of major regulating ES (Maes et al., 2012; Schröter et al., 2005). Particularly in mountains, LUCC causes severe soil erosion and water quality degradation through sediments in combination with excessive nutrient exports due to high fertilizer use (Foley et al., 2005; Montgomery, 2007). Because the provision of ES is increasingly considered in policy making (Daily and Matson, 2008), environmental policies and management programs must therefore take into account the various potential outcomes involved in land use decisions and require a-priori balancing of multiple region-specific ES indicators (Kremen, 2005; Viglizzo et al., 2012). Dynamic LUCC models such as cellular automata (CA), which reflect complex systems of LUCC, could be adopted to assess hydrological responses from LUCC impacts such as water management plans to gain insight into the dynamics and patterns of LUCC within a landscape and their hydrological impacts (Deng et al., 2015). CA based models are widely used for LUCC predictions as they can capture complex emergent behavior using a set of simple transitional rules (Clarke and Hoppen, 1997). CA simulates spatio-temporal patterns of LUCC of grid cells depending on their current status and their interactions with the neighborhood (Verburg et al., 2004; Veldkamp and Lambin, 2001; Wu, 1996). Because CA models simulate spatial and temporal LUCC quantitatively (Balzter et al., 1998), they can be used together with other models to simulate the impacts of possible LUCC on regional and local ES provisioning. LUCC in an upland catchment does not only impact local ES, but can have immense consequences for remote water users, e.g., through pollution of downstream drinking water aquifers and reservoirs. Hydrological models such as the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Gassman et al., 2007) account for the upstream-downstream connectivity within complex watersheds and allow the prediction of LUCC impacts on water related ES remote from their sources. SWAT is widely used to estimate LUCC impacts on water resources (Arnold et al., 2012; Gassman et al., 2007) and has been coupled with LUCC models (e.g., Deng et al., 2015; Kim et al., 2013; Marshall and Randhir, 2008; Memarian et al., 2014; Park et al., 2011a; Zhang et al., 2013; Zhang et al., 2016). These studies focused on LUCC under climate change (Deng et al., 2015; Kim et al., 2013; Park et al., 2011a; Zhang et al., 2016) or environmental policy scenarios (Zhang et al., 2013). However, the adoption of different types of policy instruments such as payments for ecosystem services (PES) (e.g., Engel et al., 2008) or command-and-control regulations still raise questions about their efficiency and targeting to achieve the proposed conservation goals (Engel et al., 2008). We present a modeling framework that simulates LUCC and ES as a consequence of different types of environmental policy instruments through a combination of CA based LUCC and hydrological modeling. We developed the CA model based on multinomial logistic regression (MNL) and neighborhood interactions to simulate possible LUCC for the next 50 years (2006-2056) under four different types of policy scenarios. We combined the output of the CA with SWAT to simulate water related ES (Francesconi et al., 2016) as a response of the policy-induced LUCC.

3.2 Materials and methods

3.2.1 Study area

We applied our modeling framework to the Soyang Reservoir watershed located in Gangwon Province in the North Eastern mountain range of South Korea (Figure 3.1). LUCC in the watershed through de/reforestation, agricultural expansion, and a steadily growing urbanization has led to severe water quality degradation of the country's largest drinking water reservoir, which is the main fresh water provider for half of the population including the Seoul metropolitan area (Kim et al., 2000; Maharjan et al., 2016). Therefore, several environmental regulation and protection zones have been established, such as natural conservation areas around the Soyang Reservoir and national parks in the Seorak and Odae Mountains (Figure 3.1) (Kim, 2006). However, to invigorate local economic development and income in the Gangwon Province, highland agriculture, especially the production of commercial crops, has expanded into mountainous areas due to governmental support (Lee, 1990). Water pollution through sediment and nutrient loads originating from agricultural land have been identified as the main source of declining water quality since the 1980s (Park et al., 2010). Highland agricultural activities in upstream catchments such as the Mandae and Jawoon Stream watersheds have intensified during the last decades, now covering about 54% of the total dry field area (Figure 3.1) (Kim et al., 2014a). These highland production “hotspots” are the main contributors of sediment and nutrient loads with substantial impacts on downstream ecosystems and the trophic state of the reservoir (Park et al., 2010). Especially for the Mandae Stream watershed (often referred to as Haean catchment), high erosion rates and nitrogen losses have been reported during heavy rainstorm events during the East Asian Summer Monsoon (e.g., Arnhold et al., 2013; 2014; Kettering et al., 2012; Kim et al., 2014b; Ruidisch et al., 2013). After extreme weather events such as Typhoon Ewiniar in 2006 have caused severe damages through erosion and water supply problems (Park et al., 2011b), the Korean government implemented a set of comprehensive countermeasure programs including a reforestation program for marginal agricultural lands in 2008 to mitigate water erosion and pollutant exports from highland areas. However, the long-term effects of those programs are difficult to estimate due to the various social-economic drivers of LUCC. Thus, the CA-SWAT modeling framework presented here aims at providing insights in the LUCC dynamics and the efficiency of different policy scenarios to restore ES in the watershed.

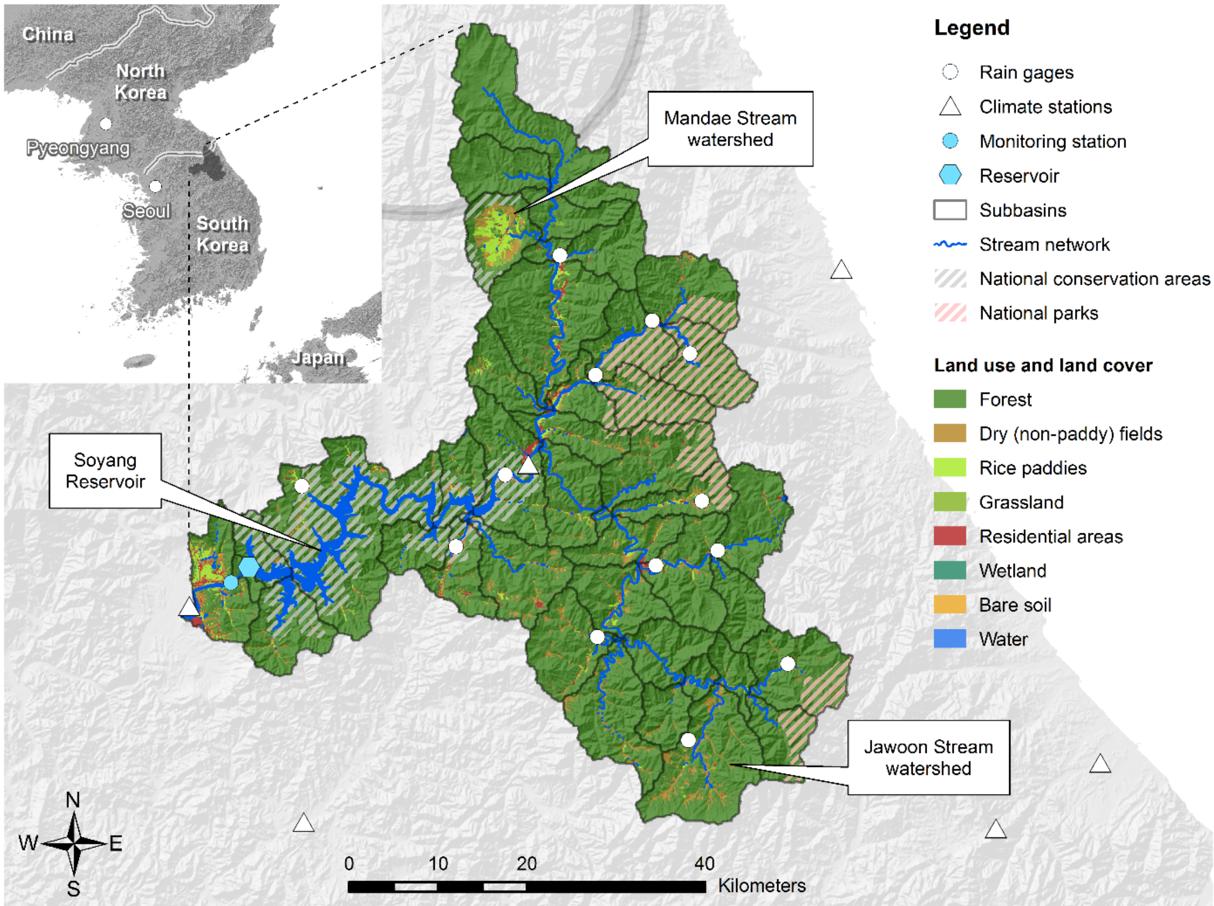

Figure 3. 1 Location and land use and land cover classification of the Soyang Reservoir watershed including subbasin configuration and climate and monitoring stations required for the hydrological modeling with SWAT. The Mandae and Jawoon Stream watersheds are the two major agricultural production "hotspots" mainly responsible for water quality degradation of the Soyang Reservoir (Arnhold et al., 2014; Park et al., 2010).

3.2.2 Conservation policy scenarios

Among the environmental policy instruments, land use zoning is a widely used command-and-control regulation tool, which involves setting zones where LUCC is prohibit or promoted (Le et al., 2010). Another important instrument aims at providing economic incentives to farmers (or other land use actors) to change their behavior, referred to as PES (Engel et al., 2008; Tomich et al., 2004). We assess three possible policy intervention scenarios proposed by the Korean government to conserve future ES in the watershed: a reforestation program through direct payments to farmers (REF), a forest protection program for high-slope areas (PRO), and a combined policy of reforestation and protection (R+P) for a 50-year time period, i.e.

from 2006 to 2056, with 10-year time intervals (Table 3.1). We compare simulated LUCC results of those scenarios with the current development trend assuming the continuation of past LUCC patterns from 1995 to 2006 under no policy intervention (scenario NO). Under REF, the currently ongoing direct payments to farmers for purchasing marginal agricultural land at elevations above 400 m and slopes higher than 15° for reforestation are continued (Jun and Kang, 2010), randomly assigned 500 ha per 10-year time interval. This policy program has reconverted agricultural areas of up to 50 ha every year due to limited financial resources and farmers' participation. Although PES are efficient tools to conserve ES compared to other policy instruments (Engel et al., 2008), they can result in externalities by private actors' behaviors (Jack et al., 2008). To complement and/or modify this PES policy, we also consider command-and-control regulation as an alternative option. PRO restricts marginal forest areas from conversion to agriculture on slopes higher than 15°, which have been identified as areas most vulnerable to soil erosion. It is a direct regulation policy for forest areas to prevent agricultural conversion and human interventions, which can show more efficient results over a long term (Miteva et al., 2012). The R+P scenario combines reforestation payments with strict enforcement of forest protection, which complement both PES and regulation policies.

Table 3. 1 Description of the four conservation policy scenarios

Policy scenario	Description
No intervention (NO)	Continuation of current land cover change trend from 1995 to 2006 without policy intervention
Reforestation (REF)	Reforestation policy for highland agricultural areas with high slopes (> 15°) and elevation (> 400 m) up to 500 ha for reforestation based on current reforestation policy
Forest protection (PRO)	Forest protection with high slope areas under current land cover change trend (> 15°)
Reforestation and protection (R+P)	Both reforestation and protection implemented

3.2.3 Modeling LUCC with CA

CA models simulate the spatial interactions of various LUCC processes (White and Engelen, 2000) and endogenous changes of status and numbers of cells for each time step based on cellular dynamics (Verburg et al., 2004). CA models are based on transitional rules that change the state of cells based on the spatial characteristics of the current cells and their interactions with the neighborhood (Wu, 1996). Transition rules in the CA are calculated as transitional probabilities of changing a cell's land cover (LC) type. We calculated the transitional probability of a cell from LC type *i* to LC type *j* at time step *t* as follows (Feng et al., 2011; Liao et al., 2016; White and Engelen, 1993; Wu, 2002):

$$S_{ij}^{t+1} = \int (S_{ij}^{t}, \Omega_{ij}^{t}, Con, N) \tag{3.1}$$

In the transition function *ʃ*, states of cell ij for the next time period with $t + 1(S_{ij}^{t+1})$ are determined by the states of cell ij during a specific time t (S_{ij}^{t}), neighborhood function of cell (Ω_{ij}^{t}), LUCC constraint factors *(Con)*, and cells number *(N)* (Feng et al., 2011).

We developed our CA model using the NetLogo software (Ver. 5.3.1). Figure 3.2 shows the structure of the CA model and Table 3.2 lists the input parameters used to calculate the transition probabilities. LC states of each cell based on local transitional probabilities are calculated from results of a MNL between 1995 and 2007 (Kim et al., 2014a). For neighborhood functions, we calculated neighborhood enrichment factors (EF) proposed by Verburg et al. (2004) with the neighborhood extent having the strongest neighborhood effect. As Kim et al. (2014a) calculated the factors for major LC types (urban, forest, agriculture), we adopted the neighborhood extent with the highest enrichment values as neighborhood boundaries. Spatial ranges of local interactions between neighboring cells are set by these EFs and values are calculated based on White and Engelen (2000). We use the circular neighborhood size to calculate neighborhood factors within their radius boundary, which is adopted in many CA-based LUCC models (e.g., Barredo et al., 2003; Cheng and Masser, 2004; He et al., 2008; Li and Yeh, 2000; Mao et al., 2013; White and Engelen, 1993). Because the circular neighborhood considers all neighborhood directions equally, it can perform neighborhood effects effectively (Li and Yeh, 2000). The neighborhood conversion probability of a cell from interactions with neighboring cells is calculated by the proportion of the sum of specific LC (k) cells to the total number of cells within the circular neighborhood range r, which is adapted from rectangular neighborhood probability functions defined by Feng et al. (2011) and Liu et al. (2008). We defined eight LC classes for the watershed (forest, dry (non-paddy) fields, rice paddies, grassland, residential areas, wetland, bare soil, and water) (Figure 3.1). However, transition was only allowed for six LC classes. Water bodies and wetland areas are fixed in the model and were not allowed to be converted. Residential areas are set as constraint areas because urbanization is a common pattern in sub-urban areas of South Korea and reconversion to forest or agriculture is very unlikely to occur. Once cells are converted to residential areas, they cannot be converted to other LC types anymore. Constraint factors are also set for forest areas designated as conservation or reforestation areas. In these areas, LC transition processes are stopped and they maintain their LC type after they are converted by policy effects.

The model is calibrated and validated to generate optimal simulation results under current parameters and probability functions. The calibration of the model was performed by adjusting model parameters and transitional change rules (Torrens, 2011). To reflect urban expansion and remaining large-scale farm and forest areas, we keep current urban areas and clustered forest and agricultural areas as fixed areas (White and Engelen, 2000). Validation of the CA model is conducted by assessing the performance of the output of models quantitatively by assessing location accuracy, which estimates the similarity and difference between model outputs and the actual status (Al-Ahmadi et al., 2013; van Vliet et al., 2016). To validate the CA model with the location accuracy method, we used the three-map comparison method, which quantifies the model's accuracy in simulating persistence and changes in pixel state (Pontius et al., 2008). This method allows comparisons between the actual map as reference 1 and simulation maps as reference 2 by calculating agreement levels from correctly simulated persistence and changes as well as disagreement levels from errors in persistence and changes (Pontius et al., 2011). The output quality of LUCC simulation models should be carefully assessed before adopting models to real world conditions because of the complex phenomena of LUCC processes and the associated high uncertainty (van Vliet et al., 2016). As an additional measure of model performance, we calculated the figure of merit, which compares observed and simulated changes to estimate the ratio of their intersections (Pontius et al., 2008). Once model validation has been performed, we simulated four different future LUCC trajectories from 2006 to 2056 with 10-year time intervals representing the four policy scenarios (NO, REF, PRO, and R+P) based on the LC configuration of the year 2006.

Table 3. 2 Description of variables of local probability used in the CA model

Variable	Computation method	Data source
Biophysical		
Summer rainfall	14-19[a] precipitation station data on annual mean values of summer rainfall (year 1995-2005), monthly resolution (Summer Monsoon period from June to August)	Korea Meteorological Administration (KMA), http://www.kma.go.kr

Elevation	Digital elevation model (DEM) with 90 m resolution (resampled from 30 m)	National Geographic Information System (NGIS), https://nsic.go.kr/ndsi
Slope	Extracted from DEM using SAGA (System for Automated Geoscientific Analyses) software	Conrad et al. (2015)
Upslope contributing area	Extracted from DEM using SAGA software	Conrad et al. (2015)
Wetness Index	Extracted from DEM using SAGA software	Conrad et al. (2015)
Distance		
Distance to river	Path distance to main Soyang River using ArcGIS 9.3	Water Resources Management Information System (WAMIS), http://www.wamis.gr.kr
Distance to stream	Path distance to tributary streams of Soyang River using ArcGIS 9.3	WAMIS
Distance to road	Path distance to road using ArcGIS 9.3	Intelligent Traffic System (ITS), http://www.its.go.kr
Distance to rural office	Path distance to rural office using ArcGIS 9.3	Google Maps, http://www.google.co.kr/maps
Distance to urban area	Path distance to existing urban areas using ArcGIS 9.3 from land cover maps (year 2006), 90 m resolution	Korea Ministry of Environment (KME), http://egis.me.go.kr
Population		
Population density	Population density of Ri[b] region (year 2006)	Korean Statistical Information Service (KOSIS), http://kosis.kr
Land zoning areas		
Natural conservation area	National conservation areas to conserve the natural environment (1 = zoning area, 0 = no zoning area)	Digitizing map data from Kim (2006)
National park	National park (1 = zoning area, 0 = no zoning area)	WAMIS

[a] Some monthly data is not possible in specific period due to technical and meteorological reasons in observation station.

[b] Ri is to the smallest administrative unit in South Korea

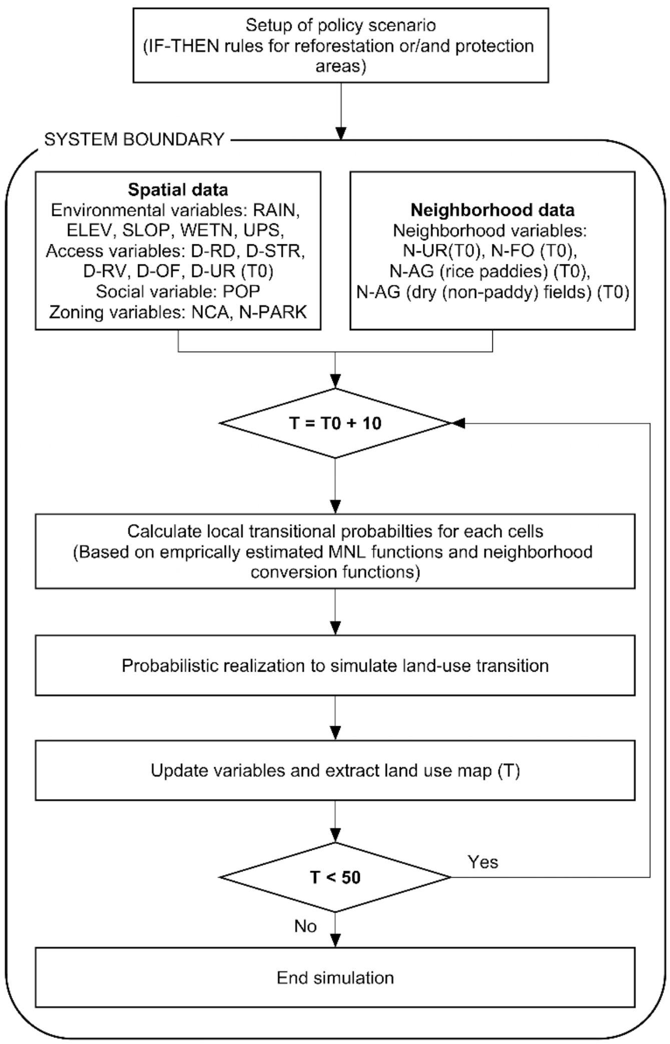

Figure 3. 2 Structure of the CA model. Local probability is calculated based on spatial data of summer rainfall (SRAIN), elevation (ELEV), slope (SLOP), wetness index (WETN), upslope contributing area (UPS), distance to roads (D_RD), distance to tributary streams of Soyang River (D_STR), distance to main Soyang River (D_RV), distance to rural offices (D_OF), distance to urban areas (D_UR), population density (POP), natural conservation area (NCA), and national parks (N_PARK). Neighborhood variables are calculated as proportion of urban (N_UR), forest (N_FO), and agriculture (N_AG) (rice paddies and dry (non-paddy) fields) cells within the neighborhood range.

3.2.4 Modeling changes in ES with SWAT

Once LUCC for the policy scenarios was quantified and its spatial distribution estimated with the CA model, the simulated LC maps were used as inputs to SWAT (Arnold et al., 1998) to evaluate the restoration potential of water related ES. SWAT is a process-based simulation model developed to simulate the impact of land use and management on water, sediment, and agricultural chemicals (Gassman et al., 2007). Although SWAT was not explicitly designed as an ES tool, its output variables can be directly related to a number of provisioning and regulating ES (Francesconi et al., 2016; Vigerstol and Aukema, 2011). We computed four biophysical indicators as proxies for fresh water provisioning, erosion prevention, and waste water treatment services (Qiu and Turner, 2013; TEEB, 2012): water yield, sediment yield, total nitrogen (N), and total phosphorus (P) (see below). In addition to its capability to quantify multiple ES indicators, SWAT was selected because it accounts for the spatial distribution of ES production and beneficiary units through the hydrologic connectivity between upstream and downstream areas (Fisher et al., 2009; Vigerstol and Aukema, 2011). A watershed in SWAT is partitioned into multiple sub-basins which are further subdivided into Hydrologic Response Units (HRUs) that comprise a combination of unique LC, soil, and management conditions (Neitsch et al., 2011). SWAT first computes the land phase processes including hydrology, erosion, nutrient cycling, and plant growth at the HRU level and calculates for each sub-basin the amount of water, sediment, and nutrients transported to the channel (Neitsch et al., 2011; Strauch and Volk, 2013). The routing phase then computes the downstream transport of water, sediment, and nutrients through the channel network to the watershed outlet taking into account instream changes and transformation processes (Neitsch et al., 2011).

We used the ArcSWAT 2012 interface with SWAT 2012 (Rev. 622) to set up and parameterize the model for the Soyang Reservoir watershed using the input datasets listed in Table 3.3. We divided the watershed into 45 sub-basins using a drainage threshold value of 3400 ha. This threshold resulted in an average sub-basin area of approximately 2% of the entire watershed area, which was considered adequate for the simulation of sediment, N, and P (Jha et al., 2004). The dam of the Soyang Reservoir and a monitoring station near the outflow of the dam were added for later model calibration and validation (Figure 3.1). To represent the hydrologic conditions of the reservoir, we used the following parameter values provided by the Korea Water Resources Corporation (K-water). We set the surface area to 65.9 km^2 and 61.8 km^2 and the water volume to $2900 \cdot 10^6$ m^3 and $2550 \cdot 10^6$ m^3 for the emergency and principal spillway, respectively. Initial water volume at the beginning of the simulation was set to $1483 \cdot 10^6$ m^3 and for reservoir outflow we used observed daily release records. After parameterization of the sub-basins and the reservoir, we further subdivided the watershed into 3270 HRUs by overlaying the soil with the LC map of the year 2006 (BL scenario) without further partitioning into slope classes. The full number of HRUs was used without threshold definitions and refinements to account for the entire landscape heterogeneity of the watershed. Once HRUs were defined, we applied the following management modifications for the different LC types. We removed the harvest and kill operation for forest, wetland, grassland, residential, and barren land and replaced it with a harvest only operation for grassland and residential areas. For dry (non-paddy) agriculture and rice paddies, we created new operation schedules to reflect the typical local agricultural management practices (Table 3.4). We selected cabbage as a representative crop for dry agriculture because it covers the largest area of dry fields in the Gangwon Province after soybean (Lee et al., 2016). In contrast to soybean, cabbage, with its short growing period and high fertilization requirements, reflects also other locally important cash crops such as radish. Type, number, and timing of operations listed in Table 3.4 were adopted from Shope et al. (2014) and Maharjan et al. (2016) who compiled local management information for different crop types from various sources including interviews, field observations, published literature, and governmental reports. Fertilizer N and P application rates were calculated from total N fertilizer inputs for local crops reported by Kettering et al. (2012) and typical N to P ratios of commonly used fertilizers (Berger et al., 2013a;b; Kettering et al., 2013). To accurately reflect biomass development and crop yields, we adjusted the number of heat units to maturity, the radiation use efficiency, and the harvest index for cabbage and rice. Biomass and yields were obtained from plot experiments conducted in the study area described by Arnhold et al. (2014), Kettering et al. (2012), and Lindner et al. (2014). Observed average aboveground biomass and yields were 8.0 t ha^{-1} and 5.6 t ha^{-1} for cabbage and 17.1 t ha^{-1} and 8.1 t ha^{-1} for rice (Arnhold et al., 2014; Kettering et al., 2012). To approximate these values, we applied 1200 and 1800 heat units to maturity, 34 kg ha^{-1} megajoule (MJ) m^{-2} and 65 kg ha^{-1} MJ m^{-2} radiation use efficiency, and harvest indices of 0.7 and 0.5 for cabbage and rice, respectively. Another modification made for cabbage was the adjustment of the initial Universal Soil Loss Equation (USLE) cover-management (C) factor, which was set to 0.13 based on the work of Arnhold et al. (2014) who studied local vegetation characteristics of cash crops and their impacts on soil erosion. For rice, we additionally changed the initial Soil Conservation Service (SCS) Curve Number to 78 and the USLE support practice (P) factor to 0.1 to account for the terrace structure of paddy fields (Jung et al., 2004; Kim et al., 2008).

Table 3. 3 Principle SWAT input datasets for the baseline Soyang Reservoir watershed model.

Data type	Description and resolution	Data sources
Digital elevation model	90 m resolution (resampled from 30 m)	National Geographic Information System (NGIS)
Stream network	National rivers and local tributary streams	Water Resources Management Information System (WAMIS), http://www.wamis.gr.kr
Reservoir	Dam outflow and storage volume, daily resolution	Korea Water Resources Corporation (K-water), https://www.kwater.or.kr
Soil map	National soil map, 1:25 000 resolution	Korea Rural Development Administration (KRDA), http://www.rda.go.kr
Land use and cover map	8 land cover types (year 2006), 90 m resolution	Korea Ministry of Environment (KME), http://egis.me.go.kr
Climate	19 precipitation stations and 6 climate stations (years 2003-2007), daily resolution	Korea Meteorological Administration (KMA), http://www.kma.go.kr
Cropland management	Type and timing of tillage, fertilization, planting, and harvest	Berger et al. (2013a,b), Kettering et al. (2012), Kettering et al. (2013), Maharjan et al. (2016), Shope et al. (2014)
Crop biomass and yield	Dry weight of aboveground biomass and yield of cabbage and rice	Arnhold et al. (2014), Kettering et al. (2012), Lindner et al. (2014)
Observation data	Discharge (inflow into reservoir), sediment, total N, and total P, daily resolution	WAMIS, National Institute of Environmental Research (NIER), http://www.nier.go.kr

Table 3. 4 Management schedules for dry (non-paddy) agriculture and rice paddies used for the Soyang Reservoir model (Sources: Berger et al., 2013a;b; Kettering et al., 2012; Kettering et al., 2013; Maharjan et al., 2016; Shope et al., 2014).

Land cover	Date	Operation
Dry (non-paddy) fields	1 May	Tillage: moldboard plow (200 mm depth)
	13 May	Tillage: furrow out cultivator (25 mm depth)
	13 May	Fertilizer application: 104 kg N ha^{-1}, 46 kg P ha^{-1}
	15 May	Planting/begin of growth: cabbage (1200 heat units)
	15 June	Fertilizer application: 192 kg N ha^{-1}, 84 kg P ha^{-1}
	30 July	Harvest and kill
Rice paddies	1 May	Tillage: moldboard plow (200 mm depth)
	13 May	Tillage: rice roller (50 mm depth)
	13 May	Fertilizer application: 139 kg N ha^{-1}, 61 kg P ha^{-1}

15 May	Planting/begin growing: rice (1800 heat units)
15 June	Fertilizer application: 46 kg N ha^{-1}, 20 kg P ha^{-1}
15 July	Fertilizer application: 46 kg N ha^{-1}, 20 kg P ha^{-1}
15 October	Harvest and kill

After setup and parameter adjustments, we ran SWAT for five years from January 2003 to December 2007 with a two-year warm-up period using daily recorded climate data of 19 precipitation and 6 climate stations located within and surrounding the Soyang Reservoir watershed (Figure 3.1). We performed semi-automated model calibration and validation following the procedure given by Arnold et al. (2012). For this, we used the SUFI-2 (Sequential Uncertainty Fitting Ver. 2) (Abbaspour et al., 2007) optimization algorithm implemented in the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) (Ver. 5.1.6.2) (Abbaspour, 2014). We divided our three-year period of interest (without warm-up) into a calibration (January 2005 to December 2006) and a validation (January to December 2007) period and performed a global sensitivity analysis to identify the most sensitive parameters with respect to discharge, sediment, total N, and P. The preselection of the input parameters was based on literature reviews and previous SWAT exercises in the study area (Arnold et al., 2012; Maharjan et al., 2016; Shope et al., 2014). After sensitive parameters had been identified, we calibrated the model using recorded daily discharge into the Soyang Reservoir and measured sediment, total N, and P at the stream monitoring station near the reservoir outflow (Figure 3.1). We performed 500 model simulations for the calibration period (2005-2006) using initial uncertainty estimates for 32 selected input parameters (Table 3.5). Within these initially defined ranges, the SUFI-2 optimization algorithm performed Latin Hypercube sampling and identified the best parameter combinations for a given objective function between observed and simulated datasets (Abbaspour et al., 2007; 2015). We used Nash-Sutcliffe efficiency (NSE) as the objective function, as it is one of the best and most widely used performance indicators for hydrological models (Arnold et al., 2012; Moriasi et al., 2007; Schuol et al., 2008). The initial parameters were then iteratively updated to produce narrower uncertainty ranges centered on the best simulation until no further improvements could be achieved (Abbaspour et al., 2007; 2015; Schuol et al., 2008). Tab. 5 lists the 32 parameters that were adjusted during the SUFI-2 calibration procedure with their initial and final uncertainty ranges. After the optimum parameter ranges had been identified for the calibration period, we ran the model again 500 times for the validation period (2007) using the same ranges. To evaluate the model performance for both calibration and validation periods, we calculated the P-factor and R-factor for each of the output variables (discharge, sediment, total N, and P). The P-factor describes the percentage of observed data bracketed by the 95 percent prediction uncertainty (95PPU) band and the R-factor indicates the average thickness of the 95PPU (Abbaspour et al.; 2007; 2015; Arnold et al., 2012; Schuol et al., 2008).

Once calibration and validation for the 2006 LC configuration (BL) had been performed, we set up four SWAT models for the Soyang Reservoir watershed representing the potential future LC for the four environmental policy scenarios (NO, REF, PRO, and R+P). For each of the four models, we replaced the LC map of the year 2006 with those simulated by the CA model for the year 2056. All other input parameters including sub-basin and reservoir configuration, management schedules, and plant parameter modifications were assumed to be identical to the BL scenario and were adopted accordingly (see description above). The four future models were run with the SWAT-CUP SUFI-2 algorithm, each with 500 simulations, using the final input parameter ranges obtained during the calibration procedure for the BL scenario as listed in Tab. 5. For each of the scenarios, we computed water yield, sediment yield, total N, and P (expressed with their medians and 95PPU bands) that were transported into the Soyang Reservoir as well as the exports from the two agricultural "hotspot" watersheds (Mandae and Jawoon). Finally, the four output variables were used to estimate ES that describe the watershed's capacity to supply fresh water, erosion prevention, and waste water treatment (TEEB, 2012). A positive change in water yield for 2056 compared to 2006 represents an increase in fresh water provisioning while a negative change indicates a decline. Negative changes in sediment yield normalized by the upstream contributing area indicate prevented erosion per unit area. Negative changes of N and P expressed as concentrations represent waste water treatment per volume of water. Conversely, positive changes in sediment, N, and P can be interpreted as continued soil and water quality degradation or regulating "dis-services" (Leh et al., 2013).

Table 3. 5 SWAT parameters adjusted during semi-automated calibration with the SWAT-CUP SUFI-2 algorithm with their initial and final uncertainty ranges (Sources: Abbaspour, 2014; Arnold et al., 2011; Neitsch et al., 2011).

SWAT Parameter[a]	Description and units	Initial range		Final range	
		Min.	Max.	Min.	Max.

CN2.mgt[b] (r)	SCS Curve Number (-)	-0.3	0.3	-0.3	0.3
SOL_AWC.sol (r)	Available water capacity of the soil (mm mm^{-1})	-0.5	0.5	-0.5	0.5
SOL_K.sol (r)	Saturated hydraulic conductivity of the soil (mm hr^{-1})	-1.0	1.0	-1.0	1.0
ESCO.bsn (v)	Soil evaporation compensation factor (-)	0.01	1.00	0.36	1.00
EPCO.bsn (v)	Plant uptake compensation factor (-)	0.01	1.00	0.01	0.60
ALPHA_BF.gw (v)	Baseflow alpha factor (d)	0.00	1.00	0.00	0.64
GW_DELAY.gw (v)	Groundwater delay time (d)	0.0	100.0	42.5	127.7
GWQMN.gw (v)	Threshold water depth in the shallow aquifer required for return flow (mm)	0	5000	0	3043
GW_REVAP.gw (v)	Groundwater revap coefficient (-)	0.02	0.20	0.02	0.12
SURLAG.bsn (v)	Surface runoff lag coefficient	0.0	24.0	0.0	13.2
CH_N2.rte (v)	Manning's roughness coefficient for the channel (-)	0.00	0.30	0.00	0.17
USLE_C.plant.dat[b] (r)	USLE cover management (C) factor (-)	-0.3	0.3	-0.3	0.3
USLE_K.sol[c] (r)	USLE soil erodibility (K) factor (0.013 t m^{2} hr m^{-3} t^{-1} cm^{-1})	-0.5	0.5	-0.5	0.5
HRU_SLP.hru (r)	Average slope steepness of the HRU (m m^{-1})	-0.3	0.3	-0.3	0.3
SLSUBBSN.hru (r)	Average slope length of the HRU (m)	-0.3	0.3	-0.3	0.3
ADJ_PKR.bsn (v)	Peak rate adjustment factor for sediment routing in the sub-basin (-)	0.50	2.00	0.88	1.65
PRF_BSN.bsn (v)	Peak rate adjustment factor for sediment routing in the channel (-)	0.00	2.00	0.00	1.15
SPCON.bsn (v)	Linear parameter for calculating re-entrained sediment in the channel (-)	0.0001	0.0100	0.0001	0.0065
SPEXP.bsn (v)	Exponent parameter for calculating re-entrained sediment in the channel (-)	1.00	2.00	1.37	2.00
CH_COV1.rte (v)	Channel erodibility factor (-)	0.00	1.00	0.11	0.70
N_UPDIS.bsn (v)	Nitrogen uptake distribution parameter (-)	0.0	100.0	29.2	87.8
NPERCO.bsn (v)	Nitrate percolation coefficient (-)	0.01	1.00	0.40	1.00
PSP.bsn (v)	Phosphorus availability index (-)	0.01	0.70	0.01	0.46

PHOSKD.bsn (v)	Phosphorus soil partitioning coefficient (m^3 t^{-1})	100.0	200.0	133.2	199.8
P_UPDIS.bsn (v)	Phosphorus uptake distribution parameter (-)	0.0	100.0	0.0	50.3
PPERCO.bsn (v)	Phosphorus percolation coefficient (10 m^3 t^{-1})	10.0	17.5	11.4	15.5
RS4.swq (v)	Organic nitrogen settling rate in the channel (d^{-1})	0.001	0.100	0.001	0.058
RS5.swq (v)	Organic phosphorus settling rate in the channel (d^{-1})	0.001	0.100	0.001	0.062
RES_NSED.res (v)	Equilibrium sediment concentration in the reservoir (mg L^{-1})	1	100	25	75
RES_D50.res (v)	Median particle diameter of sediment in the reservoir (µm)	1	100	5	50
PSETLR1.lwq (v)	Phosphorus settling rate in the reservoir (m yr^{-1})	-10	500	0	300
NSETLR1.lwq (v)	Nitrogen settling rate in the reservoir (m yr^{-1})	-10.0	10.0	-27.2	-21.5

[a] The suffix (r) refers to relative and (v) to absolute changes of the parameter values
[b] Parameter values were varied separately for forest, cabbage, rice, and residential areas
[c] Parameter value was varied only for the first (upper) soil layers

3.3 Results

3.3.1 Model validation and performance

After LUCC driving factors were calibrated from results of MNL as statistical analysis and by the threshold of changes as conditional transitional rules, the CA model was validated using a three map comparison method to quantify model outputs for different LC types (Table 3.6). Results for forest simulation had the highest accuracy values in the CA model in calibration processes, while agricultural lands have lower values. The CA model simulates rice paddies as persistent areas in contrast to other LC types while their change areas are less correctly simulated. Dry field areas have higher accuracy in the agreement of pixels due to higher accuracy in change areas, although persistent areas are less correctly estimated. When accuracy of change prediction is estimated as figure of merit, dry fields have higher values with higher prediction accuracy than other LC types, while forest and rice paddies have lower prediction accuracy of change areas.

Overall, the figure of merit shows values acceptable to other CA models, as estimated by Pontius et al. (2008), although we simulated various LUCC processes.

Table 3. 6 Three map comparison among actual land cover maps from 1995 as reference 1 (t), maps of 2006 as reference 2 (t+1), and maps of the simulation output of 2006 (t+1).

Names of component	Forest	Rice paddies	Dry (non-paddy) fields	Overall
Persistence simulated correctly	95.5%	45.7%	36.1%	91.7%
Change simulated correctly	0.6%	7.4%	21.6%	1.5%
Total agreement	**96.1%**	**53.1%**	**57.6%**	**93.2%**
Change simulated as persistence	3.2%	39.1%	34.6%	5.6%
Persistence simulated as change	0.6%	2.6%	5.7%	0.9%
Change simulated as change to wrong category	0.1%	5.2%	2.0%	0.3%
Total disagreement	**3.9%**	**46.9%**	**42.4%**	**6.8%**
Figure of merit	**13.5**	**13.7**	**33.7**	**18.4**

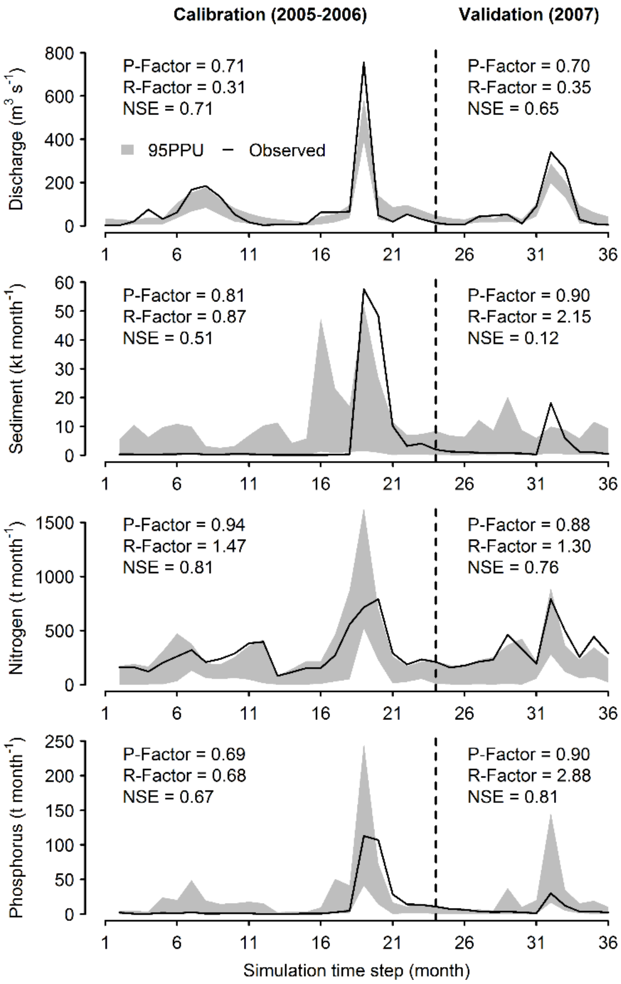

Figure 3. 3 Model performance for calibration and validation of discharge, sediment, total nitrogen, and total phosphorus. The shaded areas indicate the 95% prediction uncertainty (95PPU) band and the lines show the observed data for the total reservoir inflow (discharge), and the monitoring station near the reservoir outflow (sediment, nitrogen, and phosphorus). Note that for better readability, 95PPU and observed data are plotted for monthly time steps while performance statistics P-factor, R-factor, and Nash-Sutcliffe Efficiency (NSE) refer to daily calibration and validation.

The SWAT model shows an overall satisfactory performance as indicated by the P-factor, R-factor, and NSE values for the different output variables (Figure 3.3). The P-factor (observed data bracketed by the 95PPU) should ideally have a value close to 1, indicating that all observed data are captured by the uncertainty range, and the R-factor (thickness of the 95PPU) should be near 0, indicating that the simulated data coincide with the observed (Abbaspour et al., 2007; 2015; Arnold et al., 2012; Schuol et al., 2008). In practice, a P-factor of 0.7 or greater and R-factor of 1.5 or smaller are considered as satisfactory (Abbaspour et al., 2015; Schuol et al., 2008). The NSE (goodness of fit between observed values and best simulation) indicates satisfactory model performance when it exceeds a value of 0.5 and very good performance for values greater than 0.75 (Arnold et al., 2012; Moriasi et al., 2007). For both the calibration and the validation period, the P-factors and R-factors in Fig. 3 indicate reasonable performance for almost all variables except sediment and P, where R-factors exceed the threshold for validation. Also, the NSE indicates satisfactory to very good model performance for both periods and all variables, except for sediment validation. We attribute the large R-factor and low NSE mainly to exceptionally high sediment and nutrients records due to Typhoon Ewiniar hitting the Korean peninsula in 2006 (Arnhold et al., 2014; Park et al., 2011b). The high peaks in the summer of 2006 limited the narrowing of the parameter ranges during calibration and resulted in wide uncertainty bands relative to the observed data for the validation period 2007 (Figure 3.3).

3.3.2 Impact of conservation policies on LUCC

Because of the highly mountainous topography and limited accessibility of a large proportion of the watershed, LUCC is concentrated primarily in relatively small areas mainly along the rivers and in the lowlands. For all policy scenarios, we simulated an increase in residential areas and forest regrowth for the year 2056 and a decrease of agricultural area including dry cash crop plantations and rice paddies (Table 3.7, Figure 3.4). Regardless of environmental policy, residential areas will continuously grow until 2056 by about 25% while fallow (bare soil) and grassland areas will decrease by more than 50%. Although forest regrowth was simulated for all scenarios, its magnitude is clearly controlled by the implemented policy. The current trend scenario without intervention (NO) will result in only 0.9% increase while the combined reforestation and protection scenario (R+P) will achieve 2.7% forest regrowth by 2056. Forest protection (PRO) shows a much higher efficiency in forest regeneration than the reforestation program (REF). Simulated forest regeneration will occur at the expense of cropland, where primarily dry crops show distinct policy effects between only 5% decrease for NO and up to 43% for the R+P policy. Rice paddies will lose relatively similar areas under all scenarios, between 19% (NO) and 23% (R+P).

Table 3. 7 Simulated land use and land cover changes between 2006 and 2056 in the entire Soyang Reservoir watershed for the different policy scenarios, no policy (NO), reforestation (REF), forest protection (PRO), and reforestation and protection (R+P), compared to the baseline (BL) scenario.

Land cover	2006 (BL) Area (ha)	2056 (NO) Change (%)	2056 (REF) Change (%)	2056 (PRO) Change (%)	2056 (R+P) Change (%)
Forest	233295.4	+0.88%	+1.83%	+2.04%	+2.70%
Dry (non-paddy) fields	10615.86	-4.80%	-24.02%	-28.75%	-42.99%
Rice paddies	4536.81	-19.35%	-22.24%	-21.51%	-22.74%
Grassland	1767.42	-55.09%	-55.91%	-57.01%	-53.99%
Residential areas	3143.61	+25.46%	+26.08%	+25.33%	+24.22%
Bare soil	1088.64	-46.98%	-49.78%	-47.69%	-46.80%

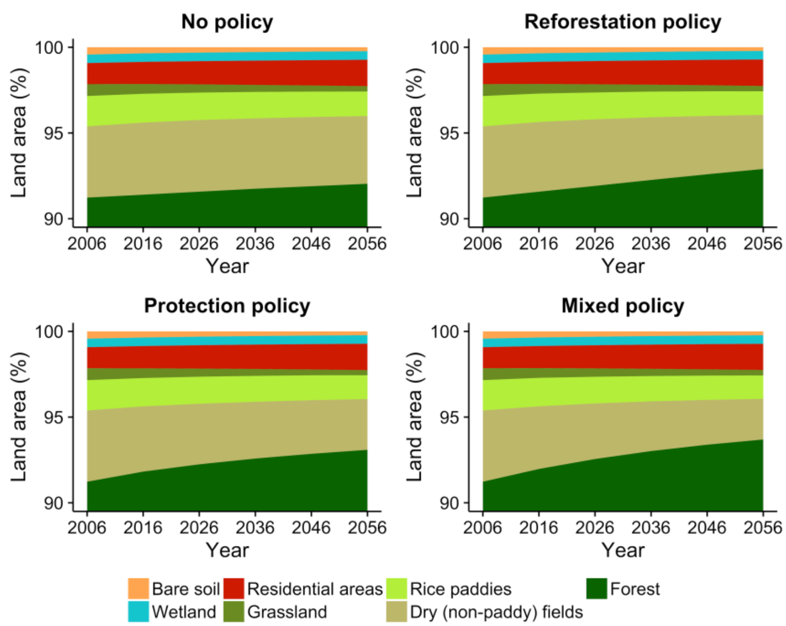

Figure 3. 4 Simulated land use and land cover changes from 2006 to 2056 for the whole Soyang Reservoir watershed for the different policy scenarios, no policy (NO), reforestation (REF), forest protection (PRO), and reforestation and protection (R+P).

Although the magnitudes of LUCC follow a common trajectory towards forest regrowth and cropland contraction under all policy scenarios, the spatial distribution reveals more distinct patterns for individual sub-regions. We found that the currently agriculturally dominated headwater catchments, i.e., the Mandae Stream and Jawoon Stream watersheds will show the most pronounced differences between the policies (Figure 3.5 and 3.6). In contrast to simulated LUCC in the entire watershed, dry (non-paddy) fields in these production "hotspots" will steadily increase by 18% through expansion of existing farms into neighboring forest and grassland areas, if no policy interventions interrupt the current LUCC trend (NO scenario). This is especially the case for agricultural areas with high elevations of about 900 m in the Jawoon Stream watershed (Figure 3.6b). Under these circumstances, no forest regeneration will occur and existing natural vegetation may be further degraded. On the contrary, if reforestation programs are implemented (REF scenario), dry fields in Mandae and Jawoon will decrease by 13% until 2056. In combination with strict protection of existing forests (R+P scenario), dry field contractions would increase to 31% while forests will experience up to 10% regeneration. Forest protection alone (PRO scenario) shows only little effects on cropland areas. Dry fields will be reduced by only 3% and rice paddies show almost the same pattern as under the NO scenario (Figure 3.5). However, rice paddy areas will decrease under all policy scenarios which is consistent with the results for the whole watershed.

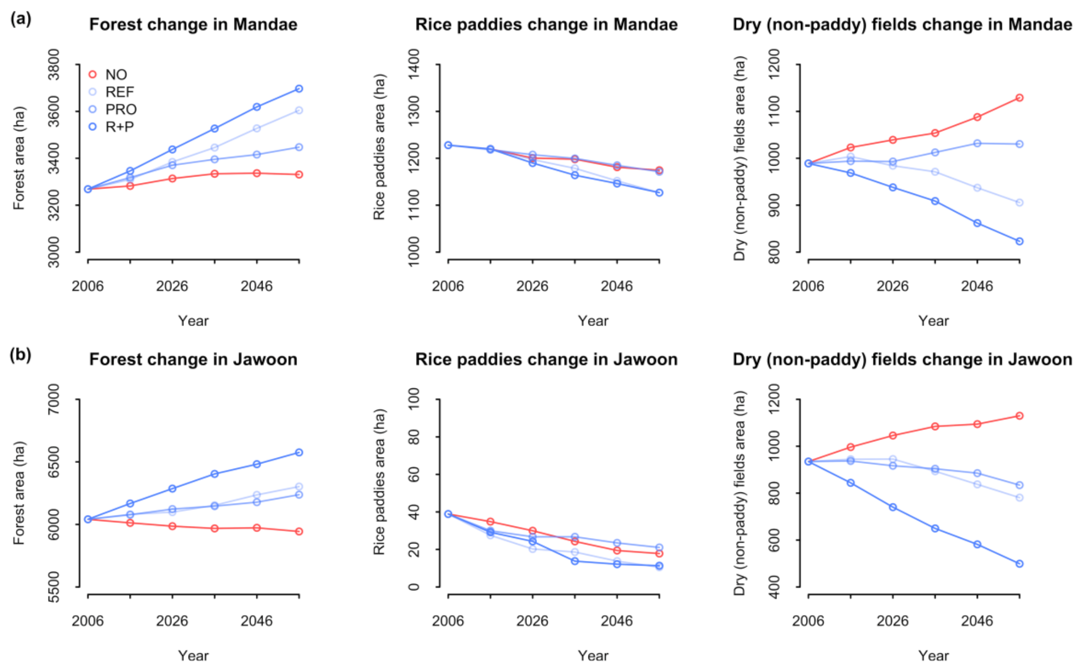

Figure 3. 5 Simulated changes in forest, rice paddies, and dry (non-paddy) field areas from 2006 to 2056 for the Mandae Stream (a) and Jawoon Stream (b) watersheds for the different policy scenarios, no policy (NO), reforestation (REF), forest protection (PRO), and reforestation and protection (R+P).

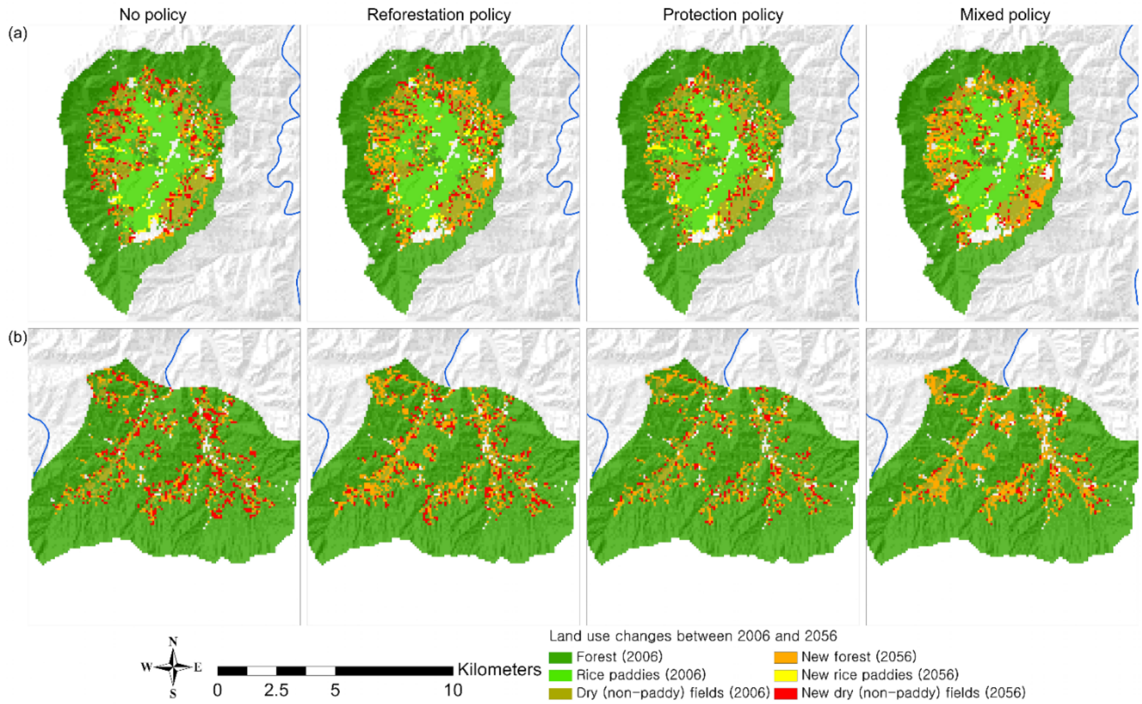

Figure 3. 6 Spatial distribution of changes in forest, rice paddies, and dry (non-paddy) field areas between 2006 and 2056 under the different scenarios, no policy (NO), reforestation (REF), forest protection (PRO), and reforestation and protection (R+P) for the Mandae Stream (a) and Jawoon Stream (b) watersheds.

3.3.2 Impact of conservation policies on LUCC

The simulated LUCC did not translate into a considerable change in fresh water provision between 2006 and 2056 regardless of the policy implemented, while proxies for regulating ES, most notably sediment yields, show clear differences between scenarios (Figure 3.7 and 3.8). While the median simulated annual water yield of the Soyang Reservoir (Figure 3.7a) remains stable at 1988 to 1989 Mm^3 yr^{-1} between 2006 and 2056 across all scenarios, median sediment inflow decreases by between 8% (NO) to 48% (R+P) from currently 1104 kt yr^{-1}. These changes correspond to between 0.3 (NO) and 2.0 (R+P) t ha^{-1} yr^{-1} of prevented soil erosion in the upstream area of the Soyang Reservoir (Figure 3.8a). Median total N inflow decreases by between 3% (NO) to 21% (R+P) from currently 2013 t yr^{-1}, and total P inflow shows a slight increase of 1% for NO, but reductions for the other scenarios of up to 30% under R+P, from currently 418 t yr^{-1}. The lower N and P inflows are equivalent to 0.03 (NO) to 0.27 (R+P) mg L^{-1} of nutrient (both N and P) removal per volume of water throughout the watershed (Figure 3.8a).

Median annual discharge of the Mandae Stream (Figure 3.7b) and Jawoon Stream watersheds (Figure 3.7c) also remain stable, while sediment, total N and P consistently increase for NO and decrease for the three conservation scenarios. Median sediment outflow of Mandae under the NO scenario increases by 9% while conservation policies yield reductions of up to 31% under R+P. The sediment reduction for R+P corresponds to 9.7 t ha^{-1} yr^{-1} of prevented erosion, while the NO scenario leads to losses in erosion prevention of 2.9 t ha^{-1} yr^{-1} of additional soil loss (i.e., "dis-service") (Figure 3.8b). Total N and P exports increase by 5% and 8% under NO respectively, which is equivalent to a "dis-service" of 0.5 mg L^{-1} of additional water pollution (Figure 3.8b). On the contrary, R+P reduce total N and P up to 17% and 19% respectively, which corresponds to 1.6 mg L^{-1} of water treatment (Figure 3.8b). Similarly to Mandae, Jawoon experiences increases of 11%, 6%, and 12% without intervention (NO) and reductions of up to 53%, 44%, and 51% under stringent conservation (R+P) for sediment, N, and P, respectively. Correspondingly, the NO scenario results in losses of erosion prevention (-1.3 t ha^{-1} yr^{-1}) and waste water treatment (-0.13 mg L^{-1}), while conservation policies, particularly R+P, prevent erosion (6.1 t ha^{-1} yr^{-1}) and water pollution (0.78 mg L^{-1}) (Figure 3.8c).

In addition to NO, REF and PRO also show clearly distinct patterns for the agricultural "hotspots" compared to the entire watershed. While sediment and nutrient loads under PRO are consistently lower for the total Soyang Reservoir inflow, REF tends to be more efficient for ES restoration in the Mandae and Jawoon Stream watersheds. The combined policy (R+P) however shows the greatest regulating effects for both "hotspots" as well as for the whole watershed. Although the median simulations indicate clear improvements in regulation ES for all three conservation scenarios (REF, PRO, R+P), the uncertainty ranges (depicted with the 95PPU in Figure 3.7) show large variabilities in sediment and nutrient loads between values close to zero to up to multiples of the medians. However, Figure 3.7 also illustrates that absolute uncertainty ranges decrease for the conservation policies indicated by a reduction of the upper boundary of the 95PPU band, most notably for sediment as well as N and P loads of the Jawoon Stream watershed (Figure 3.7c).

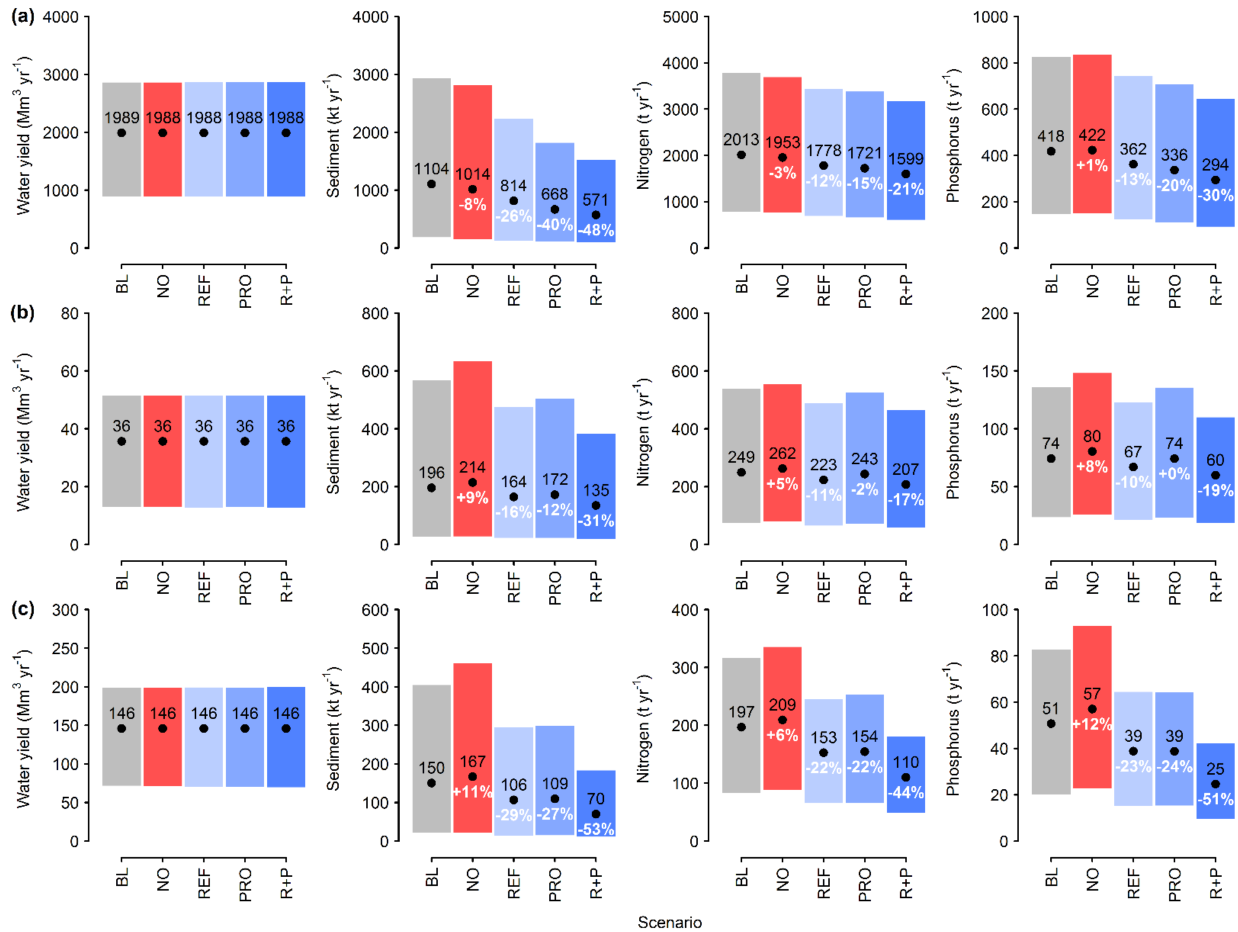

Figure 3. 7 Simulated average annual water yield, sediment, total nitrogen, and total phosphorus for the Soyang Reservoir (a), the Mandae Stream watershed (b), and the Jawoon Stream watershed (c) under the different scenarios, baseline (BL), no policy (NO), reforestation (REF), forest protection (PRO), and reforestation and protection (R+P). The bars indicate the 95% prediction uncertainty (95PPU) band and the dots show the absolute values of the median simulations (black numbers) and the percent changes compared to the baseline scenario (white numbers).

Among the two agricultural "hotspots", the Mandae Stream watershed shows consistently higher sediment and nutrient loads than the Jawoon Stream watershed, although it generates only a fraction of the water yield. Under the BL and NO scenarios, average annual concentrations of sediment, total N, and total P in the Mandae Stream exceed those of Jawoon by more than five times and those of the Soyang Reservoir inflow by between seven (total N) and ten times (sediment and total P). Monthly sediment and nutrient concentrations show even greater differences between the two watersheds (Figure 3.9). During peak events, maximum sediment, total N, and P concentrations (indicated by the upper boundary of the 95PPU) in the Mandae Stream can exceed more than ten times those of Jawoon. Figure 3.9 demonstrates that conservation policies, especially combined reforestation and protection (R+P) will reduce sediment and nutrient concentrations remarkably for Jawoon compared to no intervention (NO), while values for the Mandae Stream remain relatively high. Concentrations for R+P will decrease to less than half of the values for NO for the Summer Monsoon period but also for months of lower precipitation (Figure 3.9b). Moreover, the probability of the occurrence of extreme erosion and water pollution will be substantially lower for Jawoon, while the differences between NO and R+P for Mandae will be only moderate. Thus, the relative contribution of the Mandae Stream watershed to the total sediment and nutrient loads of the Soyang Reservoir will increase. Although conservation policies generate greater absolute erosion prevention and water treatment services for Mandae (Figure 3.8b and c), they tend to be more efficient for Jawoon with regards to overall soil protection and water quality improvement.

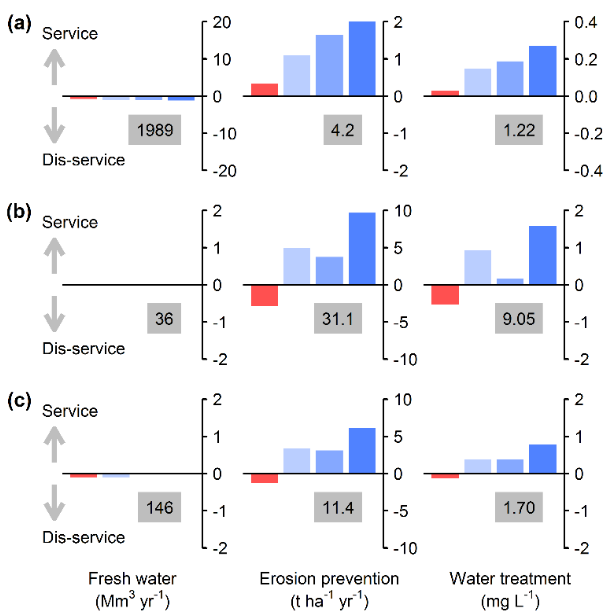

Figure 3. 8 Fresh water provision, erosion prevention, and waste water treatment services (according to TEEB, 2012) for the Soyang Reservoir watershed (a), the Mandae Stream watershed (b), and the Jawoon Stream watershed (c) for the different policy scenarios. The current trend scenario (NO) is displayed in red, and the three conservation policies in blue colors, from left to right: reforestation (REF), forest protection (PRO), and reforestation and protection (R+P). Services and "dis-services" are expressed as differences to

the baseline scenario (BL), shown in gray boxes, and refer to the median simulation runs. Note the different scales between Soyang and the Mandae and Jawoon watersheds.

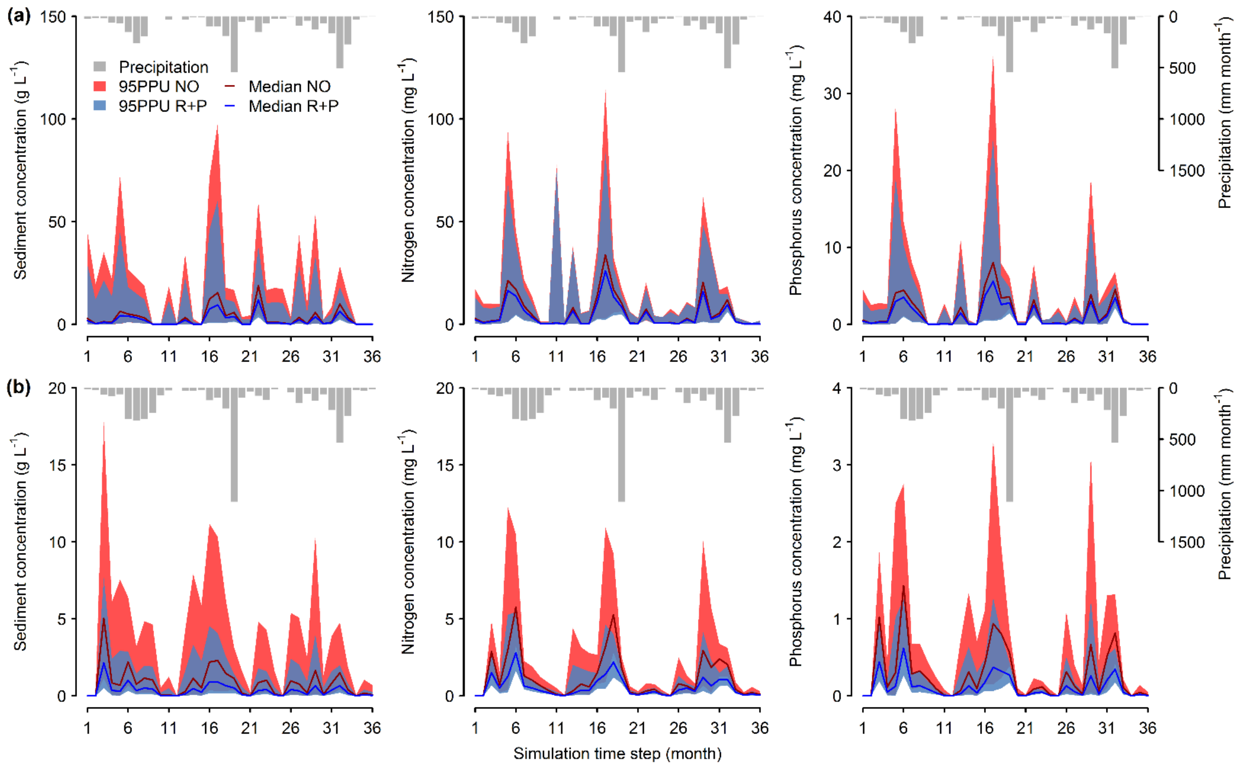

Figure 3. 9 Simulated monthly sediment, total nitrogen, and total phosphorus concentrations for the Mandae Stream watershed (a) and the Jawoon Stream watershed (b) under the no policy (NO) and reforestation and protection (R+P) scenarios. The colored shaded areas indicate the 95% prediction uncertainty (95PPU) band, colored lines show the median simulation, and the bars on the secondary y-axes refer to monthly precipitation. Note the different scales for sediment, N, and P concentrations between Mandae and Jawoon.

3.4 Discussion

3.4.1 Efficiency of conservation policies to restore ES

We found a number of LUCC developments that would occur independently of environmental conservation policies, namely the continuous decrease of fallow area (bare soil) and grassland and the steady growth of residential areas in the watershed. Regardless of the policy instrument, the size of residential areas will continuously increase until 2056 while the total population size is stagnating in downstream areas contrary to upstream agricultural areas. This development commonly known as "urban sprawl" have been fostered through rural development initiatives since 2001 by the Korean government (Jeon et al., 2013). Also, rice paddies will continuously decrease and show only relatively small responses to the type of conservation policy. Because rice cultivation has been traditionally performed primarily on suitable soils in the lowlands and on relatively gentle slopes, most paddy areas do not fall under the target area of the conservation policies. Environmental conservation policies affect primarily dry (non-paddy) fields and forest areas, which is not surprising, as these are located to a large degree mainly on steep hillslopes at high elevations that match the proposed conservation goals and standards.

All conservation policies (REF, PRO, and R+P) will result in an increase of forest cover and a contraction of existing dry field areas. As a consequence, we found that all policies show a clear tendency to enhance future regulating ES (erosion prevention and waste water treatment) in the watershed while conserving fresh water provisioning without considerable "trade-offs". The stable water provision under all policies is not surprising as the total magnitude of forest regrowth (even under R+P) will be too small to considerably alter the watershed's water balance through changes in evapotranspiration. In addition, the simulated urbanization did not cause any considerable shifts in the reservoir's inflow hydrograph or water balance components. However, we primarily found strong increases in erosion prevention and water quality regulation only when forest protection was in place (PRO and R+P), while reforestation alone (REF) results in only moderate improvements. Although REF will cause forest regeneration on sloping land and at forest frontiers due to economic incentives to farmers, for instance in agriculturally dominated catchments (i.e., Mandae and Jawoon), cropland loss will be compensated by clearing and conversion of fallow and grassland or other marginal forest areas elsewhere in the watershed. Thus, these "leakage" effects can only be avoided if reforestation programs are accompanied by stringent protection regulations as simulated for R+P.

In addition, we found that the efficiency of the conservation policies is strongly site-specific and varies with spatial scale. While we simulated a consistent moderate decline of agricultural areas and a forest regrowth for all scenarios (including NO) across the entire watershed, our results reveal a strong divergence between the scenarios for the two headwater catchments Mandae and Jawoon. Under the development trend without policy intervention (NO), these production "hotspots" would further lose their erosion prevention and water purification capacities (regulating "dis-services") while we identified a high restoration potential of ES for the conservation policies, in particular for reforestation combined with strict protection (R+P). Although prediction uncertainties for the ES proxies are relatively high, we could show that the likelihood of extreme conditions that would lead to the strongest losses in ES (i.e., the upper boundary of the 95PPU) will markedly decrease under conservation policies.

However, our results also demonstrate that the efficiency of the proposed policy programs is limited and may not necessarily meet the intended goals. The Mandae Stream watershed, which is the largest contributor of water quality degradation for the Soyang Reservoir, shows only moderate improvements. Although erosion prevention and waste water treatment services would be restored, the relative impact will still be low compared to the Jawoon Stream watershed, where substantial water quality improvements were simulated. The main reason for the low efficiency for Mandae is given by the currently limited financial resources available and lower famers' participation in the reforestation program, which allows only 50 ha per year to be reconverted. Better targeted and site-specific allocation of the available funds, for instance through PES programs (e.g., Engel at al., 2008), which concentrate reforestation incentives particularly in degraded headwater catchments, could improve the environmental performance of the conservation policies.

3.4.2 Strengths and limitations of the modeling framework

The presented modeling framework attempts to give insight into the range of consequences of alternative future environmental policies for a set of provisioning and regulating ES in the Soyang Reservoir watershed. The validation exercises demonstrate that both model components, CA and SWAT, can realistically mirror the observed LUCC patterns and water quality changes in the watershed. The modeling framework successfully captures the major drivers and spatial distribution of LUCC in headwater catchments and their role for water provisioning and regulation of downstream areas. Our findings confirm observations of previous studies that indicate the Mandae Stream watershed as the main contributor of agricultural pollution within the Soyang Reservoir watershed (e.g., Maharjan et al., 2016; Park et al., 2010). We could show that the modeling framework was able to account for a variety of impacts that can result from environmental policy programs, including unintended effects such as "leakage". It can be used to predict and evaluate performance and efficiency of proposed conservation programs and thus guide decision-making. Consequently, the quantification of model uncertainty (here given by the 95PPU bands) (Abbaspour et al., 2007) is essential in particular for decision-making. Our results demonstrate that output uncertainties can be large due to the variability of input parameters and error propagation, but provide valuable estimates of the expected ranges of impacts.

However, the presented modeling framework involves a number of limitations and simplifications. LUCC simulation was based primarily on historical LUCC trajectories and their major driving factors, but future LC and management decisions might be driven by more recent socio-economic developments in the watershed. One of these developments is the replacement of traditional crops by perennials such as fruit orchards and, more importantly, large scale ginseng cultivations by companies from outside of the watershed (Jun and Kang, 2010; Seo et al., 2014). Motivations and drivers of this trend could only be insufficiently captured by our model, but may play an important role in shaping the future LC of the watershed. Moreover, besides assumptions of the CA model, these different crop types require management practices and scheduling (e.g., fertilization, irrigation, planting and harvesting) that may be entirely different from those assumed in the presented SWAT setup. In addition, the diversity of crops in the headwater catchments, such as Mandae, is usually higher (Lee et al., 2016; Seo et al., 2014) than the assumed rice and cabbage representatives. The classification of the presented LC types, dry fields in particular, must be further refined to account for the variability of cropping systems, from monocultures to more complex multiple crop portfolios (Lee et al., 2016). Fluctuating crop prices and the elimination of protection policies for domestic rice growers (Lee et al., 2016) will become important driving factors that shape future LUCC. Changing climate will additionally affect crop choice and management decisions, but also growth patterns and yields (Ko et al., 2014), and thus, the overall future provisioning of ES in the watershed. Besides these simplifications, one major limitation of the presented work is that it covers only one provisioning (i.e., fresh water) and two regulating services (i.e., erosion prevention and waste water treatment) (TEEB, 2012), which are primarily related to water quality of the Soyang Reservoir. However, as the watershed is one of the key production areas in the Gangwon Province, future assessments must integrate the role of food provisioning, which may reveal a more pronounced trade-off with regulating ES, as in most human dominated landscapes (e.g., Maes et al., 2012; Nelson et al., 2009; Raudsepp-Hearne et al., 2010).

3.5 Conclusion

Our results demonstrate that integrated modeling that combines the dynamics of LUCC with biophysical processes within a watershed can successfully predict a variety of impacts that may result from political decisions and allows evaluating the efficiency of conservation instruments. However, the presented modeling approach requires additional refinements, in particular with respect to crop choice and management diversity (Lee et al., 2016). Moreover, the model should be complemented with additional ES indicators, most importantly food provisioning, to account for a wider range of potential synergies and trade-offs that could arise from different policy options (Nelson et al., 2009). The presented policy scenarios focus primarily on forest protection and recovery in order to restore water-regulating ES in the watershed. However, especially the role of cash crop cultivation as the main income source for local residents but also for the region's economy requires stronger consideration. As a large proportion of those cash crops in South Korea is harvested in the Mandae Stream watershed (Jun and Kang, 2010), cultivation restrictions or their replacement through stringent top-down regulations may lead to socio-economic problems and increase the resistance of farmers. Environmental policies should therefore propose a larger catalogue of measures (besides reforestation and protection) including technical approaches for on-farm erosion prevention or nutrient retention. Further research is required to assess alternative policy options for this region to achieve both environmental and social sustainability, for instance through farmers' participation. Future work should also address the effects that locally designed policy programs may cause outside their target areas. LUCC in one watershed can induce a number of impacts such as market and crop price changes that may trigger LUCC in other regions, also referred to as "telecoupling" (Liu et al., 2015). Thus, the "real" dimensions of the social-ecological consequences of environmental policies can only be assessed if one looks beyond the watershed's boundary and takes into account the full range of LUCC drivers.

3.6 Acknowledgements

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Chapter 4 Simulation of agricultural land-use changes and ecosystem services in a mountainous agricultural region using an agent-based model (ABM)

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Abstract

Agricultural activities provide various ecosystem services and dis-services such as agricultural productions, which generate soil erosion problems in mountainous regions. In the Haean catchment in South Korea, which suffers from severe soil erosion because of agriculture, the government tried promotion policies to encourage farmers to adopt perennial crops. However, perennial crops expanded less than fallow lands and ginseng farms. Under the circumstances, understanding farmers' land use and crop decisions are necessary to solve rural environmental problems. Farmers' decision-making is affected by personal characteristics, which are affected by other farmers as well as spatial attributes of their lands. We develop Agent-Based Models (ABM) to simulate changes in agricultural land use reflecting agents' decision-making and their interactions and to estimate related ecosystem services (soil erosion). The model is composed of two sub-models. One is a decision module of crop types (rice, annual, perennial) based on a multinomial logistic regression including different factors reflecting farmers' perceptions and spatial characteristics of their farmlands. The other is a fallow land decision modules based on decision trees reflecting farmers' intent and suitability values for agricultural lands. We simulate agricultural land use changes and soil erosion under four different scenarios (Baseline, fallow land expansions, ginseng farm expansions, and perennial expansions). As for crop conversion, farmers with large-sized farms convert less land to perennial crops, while others do convert to perennial crops, reflecting policies have been ineffective at promoting perennial

crops. Agricultural areas with lower value cultivation conditions are easily converted to fallow lands, which generates more severe soil erosion than other land cover types. The fallow land expansion scenario generates more soil erosion by 18% compared to the baseline scenario while the ginseng farm scenario reduces soil erosion by 20%. Based on these results, we could understand spatial patterns and farmers' decision-making for better management plans for regional agriculture.

Keywords: NetLogo, soil erosion, crop decision, scenario assessment, agent-based modeling (ABM).

4.1 Introduction

Changes in agricultural land use and management activities by human intervention such as conversion to fallow land, crop changes and reforestation are major driving factors in land use and cover change (LUCC) (Lambin et al., 2000). Agricultural land use directly affects ecosystems and their diverse services. Agricultural land use activities are mainly carried out to produce agricultural products for human well-beings, such as food, energy and raw materials. Agricultural activities also provide unintended other functions such as regulating nutrient cycles and providing habitat areas (Zhang et al., 2007; Power, 2010; Van Zanten et al., 2014). However, agricultural activities can also generate ecosystem dis-services such as habitat loss due to crop expansion as well as pesticides and nutrient runoff depending on the physical-environmental and socio-economic characteristics of the region and the cultivation system (Power, 2010). In mountainous regions, intensive agricultural activities lead to soil erosion problems, which decrease agricultural productivity and water quality across the region and water quality in downstream areas. In these regions, crop and vegetation types which provide high levels of surface soil retention are significant factors for erosion control (Arnhold et al., 2014). Especially, fallow or abandoned farmland with coarse vegetation covers can generate more soil erosion than areas with other crop types (Kosmos et al., 2000; Jain et al., 2001). Fallow lands without any cultivation or management activities are normally located in areas not suitable for agricultural activities due to their physical or economic conditions (McDonald et al., 2000; Prishchepov et al., 2013). Haean catchment, a typical mountainous catchment located in South Korea characterized by monsoon climate and highland agriculture, has experienced soil erosion and water quality problems due to agricultural land uses (Park et al., 2010). Cultivation of commercial annual crops (cabbages, radish and potatoes) in highland agriculture areas has caused severe soil erosion during monsoon periods (Jun, 2008). To reduce this problem, the government has implemented various policies, such as the application of slope management techniques to protect soil erosion from farmlands, and subsidies to convert annual farms to perennial and organic farms. The policy to promote perennial crops did indeed increase perennial farming in the region, while ginseng farms, a perennial crop but not promoted by government, and fallow land also increased due to farmers' land abandonment. Some farmers who do not have the capacity to cultivate perennial crops abandoned or sold their farmland to outsider ginseng farmers (Jun and Kang, 2010). This phenomenon of ginseng and fallow land growth could generate other problems for regional environmental sustainability. Under the circumstance, understanding of land use and crop choice processes could be used to estimate and simulate various LUCC and related ecosystem service (ES) (Mottet et al., 2006).

Models based on farmers' decision-making should reflect farmers' personal preference opinions and experience as well as spatial characteristics of farm areas (Rounsevell et al., 2003; Dury et al., 2012). Spatial modeling is an approach to understand farmers' decision-making with regards to crop and land use decisions, as well as to simulate LUCC arising from alternative land management plans (Lambin et al., 2000). In particular, simulation models can estimate LUCC under different policy interventions, which combine socio-economic and environmental interactions in agricultural systems (Parker et al., 2003). Agent-based models (ABM) model interactions between human and natural systems. These agents can have different characteristics and strategies for their decisions and interact with other agents and their environment (Bonabeau, 2002; Valbuena et al., 2010). Because ABMs are based on the decision-making of agents, ABMs are a bottom-up approach that simulates emergent phenomena of their decisions, and their interactions with each other and with their environment (An et al., 2005). Moreover, ABMs cannot only reflect temporal changes within agents' framework, but also spatial changes by generating spatial features from spatial data (Brown et al., 2005). To find out policy effects on agricultural practices, it is necessary to understand the factors influencing farmers' decision-making processes with regards to crop choice and land use. ABMs are also a useful tool to estimate spatial impacts on ecosystems because they simulate the agents' behavior under different policy options and different LUCC scenarios. Because of these advantages, ABMs are increasingly used to study social and other influences on individual decision-making in LUCC. Famers' land conversions to and from fallow lands are determined by the characteristics of farmers' preferences, which are influenced by preferences of other farmers in the network. Moreover, farmers are affected by the spatial characteristics of their farmlands (Rounsevell et al., 2003; Dury et al., 2012). Under these circumstances, it is necessary to develop an ABM of LUCC in agricultural areas to reflect conversions to and from fallow lands and to estimate possible impacts of policy scenarios on regional ecosystems.

Understandings interactions between human decision-making and natural ecosystems within a system boundary are needed to develop an ABM integrated with an assessment of ES (Matthews et al., 2007). Assessment of ES could be integrated with simulation models of LUCC and management decisions to estimate potential trade-offs between LUCC and ES (Nelson et al., 2010). Although development of integrated ABMs of LUCC and ES is still challenging, several studies exist, which mainly estimated impacts of LUCC on regionally specific ES such as carbon storage (Robinson et al., 2013), habitat provision (An et al., 2006), pollination services (Kremen et al., 2007), water supply (Bithell and Brasington, 2009) and biodiversity (Brady et al., 2012; Villamor et al., 2014). These integrated models simulate LUCC and estimate related changes in ES using existing indicators. However, water-related ES affected by agricultural LUCC do not receive a lot of attention in earlier ABM studies, although these ES are mainly affected by agricultural LUCC, which can cause soil erosion, as well as input of chemical fertilizers and pesticides (Foley et al., 2005; Montgomery, 2007; Hascic and Wu, 2006). In particular, water quality problems in the Soyang River stemmed from soil erosion due to agricultural LUCC in a mountainous watershed (Jun and Kang, 2010; Arnhold et al., 2014). Agricultural practices, which vary by crop types, cause changes of ES with regards to regulation capacity of soil erosion in the region (Arnhold et al., 2014). An assessment of soil erosion is needed to quantify changes of ES as a result of agricultural LUCC and crop choices (Angima et al., 2003). Therefore, the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997), which is widely applied to estimate quantitative soil erosion potential, could be integrated with an ABM of agricultural LUCC.

Another challenge to ABMs to estimate LUCC and ES is to solve difficulties in the implementation of realistic decision-making processes which reflect agents' land use choice (Nelson and Daily, 2010). Farmers' decision-making is not only decided by socio-economic factors and spatial features of farmland, but it is also affected by opinions of other farmers (Sun and Müller, 2013). To reflect these factors, various factors and models are applied to agents' decision-making processes and social interactions. ABM studies consistently applied several factors on farmers' decision-making processes such as economic factors (tax, income, crop price) (Hoffman et al., 2002; Milner-Gulland et al., 2006), spatial features of farmlands (Matthews, 2006; Magliocca et al., 2014) and social influence of other farmers (Deffuant et al., 2002; Chen et al., 2014; Sun and Müller, 2013). Moreover, recent studies focused on farmers' decision-making with regards to adoption of payments for ecosystem service (PES) as policy scenarios (Chen et al., 2014; Sun and Müller, 2013; Villamor et al., 2014). So far, however, there has been little consideration given to farmers' attitudes toward ES, which could be a significant driving factor in their decision, since several agricultural studies emphasized the importance of farmers' perception of ES (Bryan et al., 2010; Hatton McDonald et al., 2013; Plant and Ryan, 2013; Smith and Sullivan, 2014).

In the current situation, we developed an ABM to simulate possible LUCC and their impacts on ES by estimating soil erosion volumes. The ABM included different driving factors of farmers' decision-making, including farmers' perception of ES. To develop the model, we used farm household survey data to understand farmers' decision-making processes with regard to crop and agricultural land use choices. From the model, we estimate possible soil erosion under different LUCC processes and scenarios. The ABM, therefore, simulated regional changes of agricultural systems and their impacts on ecosystems under various scenarios, and identified conversion areas where areas vulnerable to soil erosion are located.

4.2 Methodology

4.2.1 Study area and background

The research area is the Haean catchment area in South Korea (Figure 4.1), which is designated as a water pollution source areas of Han River and Seoul Metropolitan area (Jun, 2008; Lee, 2008; Ruidish et al., 2013). The flatland of the basin is mainly used for agriculture and the surrounding areas are covered by forest. Rice paddy areas are located in flat areas. Annual dry crops are widespread and perennial crops are cultivated on comparably steeper sloped areas (Poppenborg and Koellner, 2013). Typical annual agricultural crops are radish, beans, potatoes and cabbages, called highland crops, which are major income sources for farmers.

Among perennial crops, bellflowers and fruit orchards are mainly cultivated by local farmers, while ginseng farms are mainly cultivated by outsiders and have rapidly grown since 2005 (Jun and Kang, 2010). Because of on the prevalence of annual crops and extreme rainfall in the monsoon period, the catchment area generates more severe soil erosion than other areas in the Soyang River Basin (Park et al., 2010; Ruidish et al., 2013).

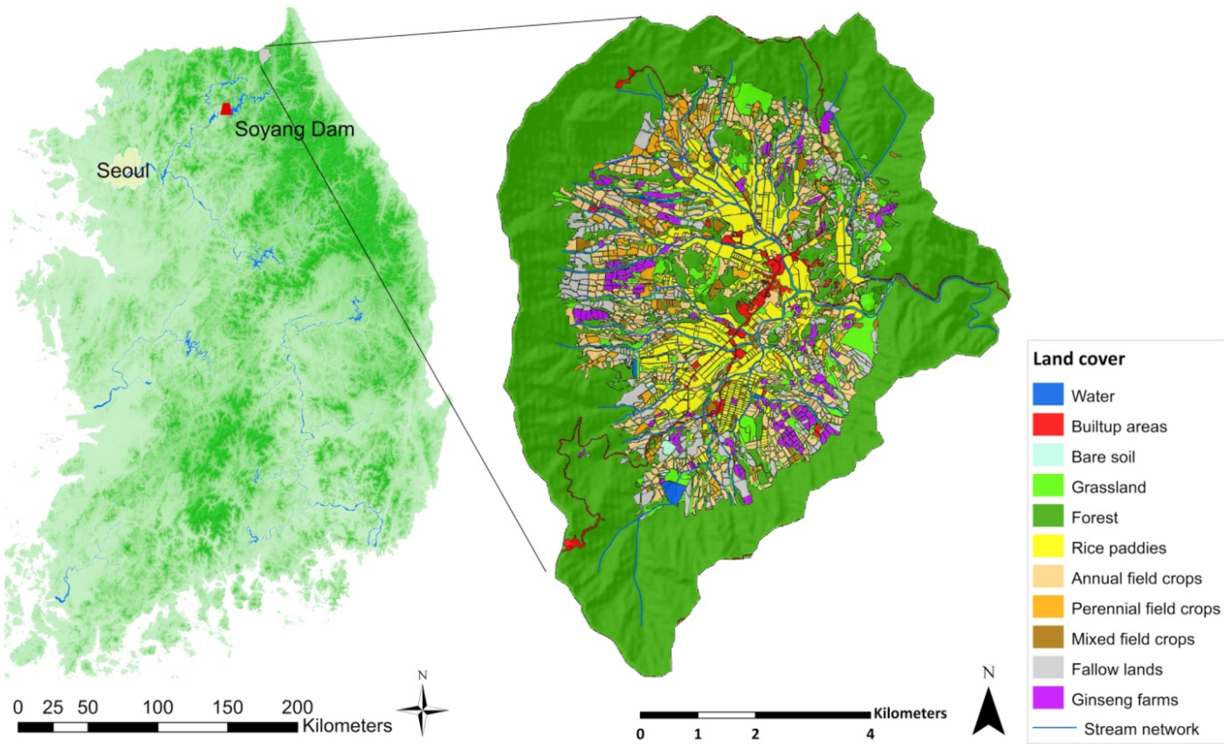

Figure 4. 1 Land-use and crop type classification in the Haean catchment. The LUCC map is produced by original survey data (Seo et al., 2014).

Since the area has been identified as a water pollution hotspot, the government has tried out various policy various programs to reduce water pollution, such as promoting perennial crops and fruit orchards, restricting addition of new soils into farms, adoption of slope management techniques and conversion of marginal farms to forests. Among these policy programs, the orchard promotion policy was received favorably and effectively by the local community (Jun and Kang, 2010). This policy could reduce soil erosion and stabilize soil conditions under recently improved cultivation conditions due to climate change. As highland annual farms decreased in extent due to recent growth in perennial crops, these areas experienced various transitional agricultural land uses. Some farmers who did not have the capacity to convert from annual to perennial crops abandoned their farmland to fallow lands. Some of this farmland has been sold to outsiders, who wanted to use it for ginseng farms and therefore ginseng farms have increased rapidly in the catchment since 2002 (Jun and Kang, 2010). Because it is necessary to estimate the impacts in these changes of land use and crop choices on regional ecosystems, we developed agricultural LUCC models for different scenarios and estimated the impacts of LUCC.

Table 4. 1 Land use and crop changes in Haean catchment between 2009 (column) and 2010 (row) (km^2) based on land use maps based on field survey data on a yearly basis (Seo et al., 2014).

2010 \ 2009	Other land	Rice paddy	Annual	Perennial	Ginseng	Undefined	Fallow land
Other land	45.16	0	0.10	0	0	0.01	0.11
Rice paddy	0	5.17	0.06	0	0.07	0	0.19
Annual	0.23	0.01	4.63	0.36	0.52	0.28	1.47
Perennial	0.01	0	0.16	0.92	0.03	0.16	0.06
Ginseng	0	0	0.01	0	0.70	0	0.07
Undefined	0.08	0	1.41	0.09	0.16	0.70	0.29
Fallow land	0	0	0.18	0.01	0.11	0	0.83

4.2.2 Agent-based model for decision-making of agricultural household

4.2.2.1 Farmers' data

A farm household survey was conducted in 2010 to investigate farmer' perception of ES and economic factors influencing their agricultural land management (Poppenborg and Koellner, 2013). The survey had 220 respondents, which corresponds to 33% of all farmers in the catchment. The survey collected farmers' behaviors related to crop choices, such as their attitudes to ES, behavioral control factors and social factors that influence crop choices, and the farmers' cultivation intent for crops (rice, annual, perennial crops). In addition to this, information on farmers' social and economic status was also gathered such as subsidy support and participation in the farmers' capacity building program (CBP). The survey was combined with spatial data on agricultural land use and crop status as well as physical data (slope, elevation, soil properties, neighborhood land use status) using geographic information system (GIS). Then we used these farmers as agents in an ABM, which created 238 agents and duplicated them, resulting in a total of 441 random agents to realize similar numbers of farm households in the catchment. Agents have personal attitudes toward specific ES (biomass production, water quality and soil erosion) and behavioral control factors (agricultural skill and knowledge and legal legislation) with regards to each crop type (rice, annual and perennial crops) (Poppenborg and Koellner, 2013). They also have their own intend values to make a particular crop decision, which reflects their preference and willingness. These agent' features are quantified from 1 to 5 according to personal importance and consideration. Spatial features of the farmlands are also applied quantitatively through grid-cell based spatial data and LUCC maps based on field survey data, as seen in Table 4.1, to understand LUCC and crop change patterns based on Seo et al.(2014). In the ABM framework, we developed two sub-model of decision-making process of agricultural land use and crop choices based on these agent' data.

4.2.2.2 Sub-model of farmers' crop decision

We developed a sub-model of farmers' decision-making with regards to crop choice among rice, annual and perennial crops. To develop this decision module, we applied a stochastic approach using multinomial logistic regression (MNL), which estimates the transitional probability of crop choice from various input factors from survey and spatial data. MNL can estimate the conditional probability of agents' decisions in a multinomial logistic form (Benenson and Torrens, 2004; Le et al., 2008). We, therefore, extracted coefficients (β) of each factor from the MNL analysis, then they were applied as explanatory factors. In the model, probability functions of crop choice are described as

$$P_{ij} = exp(\beta_i X_j)/\sum_{k=1} exp(\beta_i X_k) \quad (4.1)$$

where P_{ij} is the probability of crop i to be converted to crop j, β_i is a set of coefficients and X_k is a set of explanatory variables. From this calculation, each farmer has different probability values (P) of crop choice and we, therefore, have a probability range for each crop choice, which sums to 1 in total. Next, farmers will choose their crops based on the probability and generation of random values to reflect uncertainty in the agents' decision. Farmers' crop-choice for the next cultivation year (t +1) will be simulated and their land use types will be changed accordingly. For the next simulation period (t + 2), farmers update their perception of ES, control factors of crop choice and their individual intent on updated crop types using actual survey results. As for spatial variables, physical factors are fixed in all simulation steps while neighborhood land use will be updated after simulation results are applied to spatial land use maps.

4.2.2.3 Social influence module

We developed a social influence sub-model, which reflects the effect of social networks and interactions between agents on farmers' intent because agent behavior is normally influenced by others in a local community, either directly or indirectly (Figure 4.2). Direct interactions occur when agents communicate with other agents directly, while indirect interactions reflect agent behavior within the system environment which affect agents' perceptions (Sun and Müller, 2013). The social influence module consisted of two parts. One is an opinion exchange model to reflect interactions between individual agents, and the other is a network model which sets the social network boundary and links it to the environment. To develop the social influence model, we adopted an opinion dynamics and bounded confidence (BC) model (Hegselmann and Krause, 2002) to simulate each agent's interaction, and a small world network model (Watts and Strogatz, 1998) to set the network group and boundary.

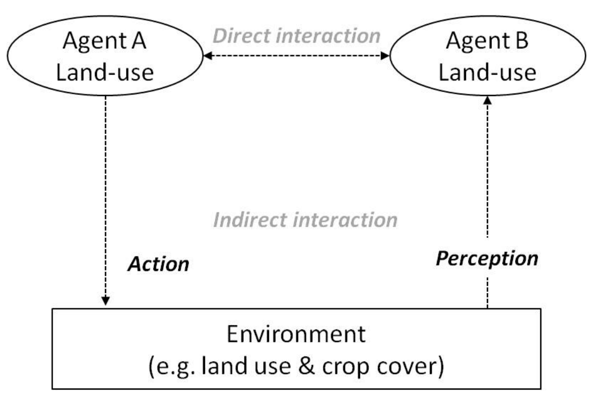

Figure 4. 2 Different types of agent' interactions (source: adapted from Sun and Müller, 2013).

Opinion dynamics under BC is an agent's interaction model, which considers characteristics of agents' interactions in the real world (Lorenz, 2007). Although agents could interact with all other agents in their networks theoretically, agents tend to interact with those who do not have significant difference in their opinions, called the BC situation (Kou et al., 2012). BC model can set an opinion threshold for the agent's interactions so that two agents have interactions. Only their opinion differences are lower than a threshold value. In particular, the Hegeselmann and Krause BC model assume that agents are affected by all other agents within the BC situation in their community network at the same time (Hegselmann and Krause, 2002; Kou et al., 2012). The model can be applied in the ABM of agricultural LUCC in the catchment for agent' interactions with regards to farmers' intent. The BC model has a formula as follows:

$$x(t+1) = |I(i, t(x))|^{-1} \sum_{j \in I(i,x(t))} x_j(t) \text{ for } t \in T, \tag{4.2}$$

where $I(i, x) = \{ 1 \leq j \leq n \mid |x_i - x_j| \leq \varepsilon_i \}$

In this formula, agent i has a confidence level of ε_i reflecting opinion gaps without agent interactions, and agent i's interaction with agent j ($|x_i - x_j|$) are calculated and then all agent i's interactions with other agents are summed. We used farmers' intent as agents' tendency in the BC model, which reflects farmers' preference and farmers, therefore, change their intent when they communicate with other farmers.

To set the network boundaries, we applied a small world network model, which can be combined with opinion dynamic models (Stauffer and Meyer-Ortmanns, 2004; Suo and Chen, 2008: Sun and Müller, 2013). Our model hypothesized a small world network, i.e., most nodes are linked by a small number of edges. Each agent has higher levels of random links with other agents in the network and lower levels of links with agents outside the network (Watts and Strogatz, 1998; Costa et al., 2007). Unlike other studies, we created the farmers' network based on the location of their farmlands and distance from others instead of administrative division because the catchment is one administrative and settlement area. To model the opinion network, we estimated the network through path length and clustering coefficients as described in Appendix 4.4, which quantifies network properties. Lower path length and higher clustering coefficient are regarded as better clustering network (Watts and Strogatz, 1998).

4.2.2.4 Development and adoption of LUCC scenarios

The ABM simulated changes in crop choice and their impacts on regional ES by estimating soil erosion. As mentioned above, land use and crop choice have been changed from a few dominant highland crops to diverse crops for economic, political and environmental reasons. We developed three different policy scenarios for crop choice and land management plans based on current LUCC patterns and policy directions:

business as usual (BAU), fallow land growth (S1), perennial crop growth (S2) and ginseng farm growth (S3). The BAU scenario is a baseline scenario, which simulates crop changes under current change patterns without changes in fallow lands and ginseng farms. The fallow land growth scenario (S1) consider the situation in which fallow lands increase in areas with lower agricultural suitability. This reflects actual agricultural LUCC in the region between 2009 and 2010, which also occurred in other regions in South Korea for economic reasons (Rhee et al., 2009). From the scenario, we hypothesized the environmental aggravation in the catchment with growth in fallow lands and soil erosion. The perennial crop growth scenario (S2) assumes the conversion of fallow lands to perennial crops on land with comparably higher agricultural suitability and farmers' intent to cultivate perennial crops. This scenario hypothesizes an effective government policy for regional farmers to adopt perennial crops instead of promoting ginseng. The ginseng growth scenario (S3) reflects fallow land conversion to ginseng farms. Part of currently fallow land could be converted to ginseng farms depending on land characteristics and suitability because ginseng farms are expanding on marginal lands with lower agricultural suitability (Mok, 2005). Based on these scenarios, we simulated agricultural LUCC and crop choice and soil erosions.

To implement LUCC scenarios, we model farmers' decisions to leave land fallow based on their agricultural intent to cultivate crops and agricultural suitability of their farmlands. As agricultural abandonment normally occurs on unproductive lands in developed countries (Ramankutty and Foley, 1999), abandoned lands in South Korea also occur on areas with lower agricultural suitability, which demand higher levels of agricultural labor costs (Kim, 1996; Rhee et al., 2009). To estimate land suitability, we adopted agricultural land suitability index (LSI) based on multi-criteria evaluation (MCE) and fuzzy membership functions, which is widely used in land suitability evaluation from various environmental properties depending on various spatial characteristics of farm lands (Tang et al., 1991; Van Ranst et al., 1996; Sicat et al., 2005; Nguyen et al., 2015). According to types of input variables, the S-shaped membership function (S-MF) and the Kendal membership function (K-MF) are used to calculate LSI.

$$\mathrm{K-MF} = \begin{cases} {}^{1}\!/\!\left[1 + ((x - b_1)/d)^2\right] & \mathrm{x} < b_1 \\ 1 & b_1 < x < b_2 \\ {}^{1}\!/\!\left[1 + ((x - b_2)/d)^2\right] & \mathrm{x} > b_2 \end{cases} \qquad (4.3)$$

$$
\mathrm{S-MF} = \begin{cases} 0 & \chi \in (\gamma, +\infty) \\ 2\,[\,(\chi - \gamma)\,/\,\gamma - \alpha\,]^2 & \chi \in [\beta, \gamma] \\ 1 - 2\,[\,(\chi - \gamma)\,/\,\gamma - \alpha\,]^2 & \chi \in [\alpha, \beta] \\ 1 & \chi \in (-\infty, \alpha) \end{cases} \tag{4.4}
$$

where each threshold value for sustainability classes (b_1, b_2, α, γ) determines optimal conditions, d is b_1 - b_2 or cross point value (0.5), and $\beta = (\alpha + \gamma) / 2$. Threshold values are derived from Nguyen et al. (2015) as shown in Appendix 4.1. We combined farmers' intent values and LSI to develop decision-tree modules on fallow lands decisions under different scenarios. From the sub-modules on farmers' decision-making processes, we develop the ABM of agricultural land use and crop choices described in Figure 4.3.

4.2.3 Assessment of ecosystem services

Changes of farmers' crop decision could generate changes in ES. To simulate LUCC impacts on the regional ecosystem, we estimate changes in regional ES under different scenarios. The spatially explicit functional modeling is a systematic approach which incorporates spatially explicit models and quantitative valuation of ecosystems services (Kubistzewski et al., 2013, Costanza et al., 2014). Valuation of ES could be used to estimate impacts of land management policies and implementation of those policies under different scenarios (Costanza et al., 2014). We here estimate soil erosion control based on changes in farmers' crop decision, which is regarded as a serious environmental issue related to agricultural LUCC in the region. We used the RUSLE to estimate average soil erosion per unit area (tons/ha) per year (Renard et al., 1997). The model calculates annual soil loss from a climate factor (R-factor), erosion factor (K-factor), slope-length and slope factor (LS-factor), vegetation-cover factor (C-factor), and support-practice factor (P-factor) as follows:

$$
\text{Annual soil loss} = R * K * LS * C * P \tag{4.5}
$$

The R-factor reflects annual surface runoff due to annual rainfall and maximum rainfall intensity, which is calculated from precipitation data. The K-factor indicates resistance to soil erosion as a result of soil characteristics and structure as calculated from soil data. The LS-factor is determined by slope-length and slope-degree. The C-factor depends on the degree to which surface cover types prevent surface erosion. The P-factor depends on land-cover types of farmlands and upward and downward slope (Renard et al., 1997).

We only calculated agriculture-related soil erosion under farmers' decision-making on crop choice using different C-factors derived from earlier research. For fallow areas, we used the median values of values reported for fallow lands and grassland because fallow lands could convert to natural vegetation partially. Data for input variables and indicators are obtained from empirical observation in the research area (Arnhold et al., 2014) and literature on other regions of South Korea. The input value for each factor is detailed in Appendix 4.3.

4.2.4 Uncertainty and sensitivity analyses

ABMs necessarily have modeling uncertainty due to their complex characteristics and limited understandings of factors and processes in the human-natural systems (Ligmann-Zielinska et al., 2014). To develop ABMs, it is necessary to evaluate the model by quantifying variability and sensitivity of model outputs. The uncertainty of model outputs is normally estimated by comparing results of several model runs based on random sampling, such as Monte Carlo simulations. Sensitivity analyses are conducted by running multiple simulations of the model using extreme values of model input factors (An et al., 2005; Guzy et al., 2008; Ligmann-Zielinska et al., 2014). We conducted an uncertainty analysis based on multiple simulations of the model with random numbers in the steps of crop choice and estimates soil erosion. Sensitivity analysis is also conducted by applying random values of input factors based on their distributions in farmers' decision-making processes such as attitude towards ES and perceptions on agricultural control factors. We used a variance-based sensitivity analysis (VBSA) to estimate individual and/or combination factors' influences on model performance in socio-ecological ABMs (Ligmann-Zielinska et al., 2014). The VBSA estimates the total variance of input factors reflecting their influences and interactions by quantifying the partial variance of factors, called the first-order sensitivity index (S), and interactions between a specific factor and others, called the total effect sensitivity index (ST) (Homma and Saltelli, 1996). The VBSA helps strengthen model performance and reflect real-world changes under different scenarios (Filatova et al., 2013). In our study, we used values of ST in VBSA to estimate overall influences of the input factors, including their interactions from 14000 model runs for 12 factors. To estimate ST values, we used Sobol's sequence with quasi-random sampling and Monte Carlo integrals, which is suitable to estimate ST indices for complex and non-linear environmental models (Saltelli et al., 2010).

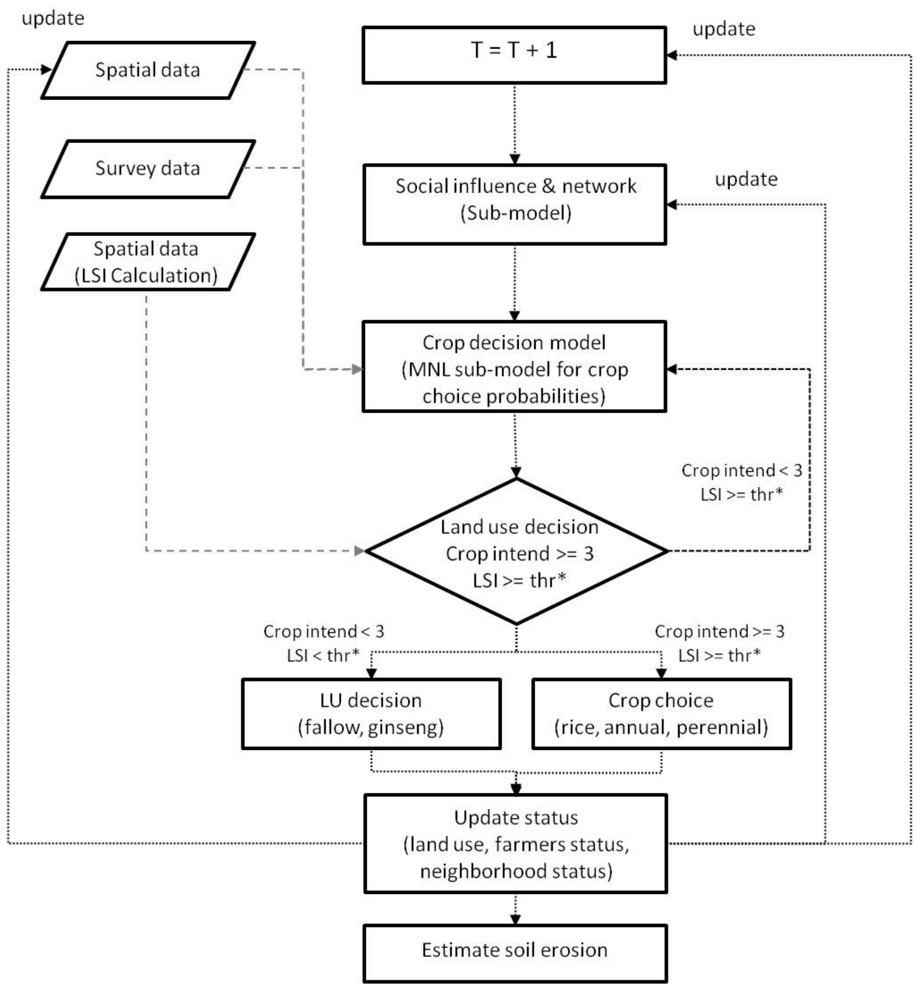

Figure 4. 3 Flow chart of ABM framework, which integrates crop decision module with multinomial logistic regression and other land uses (fallow land and ginseng) decision module with decision tree.

The overall procedure of the model is described in Figure 4.3, farmer' crop decision is the first decision module and fallow land decision is the second module based on transitional probability of crop choice by MNL and interactions with other farmers in the network. Then, the model updates regional land use and crop types and estimate possible soil erosions rates under different scenario. The development of the ABM for LUCC and crop choices was carried out using NetLogo (Wilensky, 1999). This software can simulate spatial changes in crop choice and LUCC under different scenarios and reflects agents' interaction in the system boundary. Changing model input variables in different run is used to calibrate and validate the model, and then the model simulates each scenario several times to estimate the impacts of crop choice and

LUCC. For the analysis of VBSA, we used R software including *RNetlogo* (Thiele, 2014) and *sensitivity* packages (Martinez, 2011).

4.4 Result

4.3.1 Development of farmers' decision-making model

Our model simulates changes of agricultural land use and crop choices, which are used to estimate the effects of agricultural policy scenarios. To develop the decision-making procedures, we extracted driving factors of crop choices and their coefficient values from MNL, as shown in Appendix 4.5. Attitude toward biomass production, soil erosion and water quality affected farmers' crop choices. Agricultural skills and knowledge and legal legislations were behavioral control factors of crop decisions. Elevation, slope, soil organic carbon and bulk density, as well as neighboring crop status, were extracted as spatial driving factors of crop choices. The decision model simulated conversion on farmers' crop choice on farm patches on a site-by-site basis. In the BAU scenario, rice and annual crop farmers are decreasing slowly and perennial crop farmers are increasing. However, spatial changes are different to these patterns: farmlands under annual crops expanded perennial and rice farmlands decrease, although the numbers of farmers choosing annual crops decrease. Farmers' perceptions and attitudes toward ES were also extracted as driving factors of changes from MNL.

We conducted uncertainty analysis to estimate the variability of the ABM outputs and a sensitivity analysis each factor within the ABM from multiple simulation outputs. Estimates of agricultural area is a spatial output of the model and depend on farmers' decision-making processes. And then, annual soil erosion rate is also simulated as estimates of ES. In the crop choice models, estimates of rice area and farmers have lower variability than estimates for other crops, which reflects regional change patterns. When we compare simulation results for farmers and farmland, similar levels of result variations are estimated in the model. There are differences in estimates of soil erosion rates, according to small levels of changes of crop types and their variation. Then, we examine uncertainty analysis through variability of model output of agricultural LUCC and soil loss as described in Figure 4.4. When we compare the variance of the simulation outputs in the BAU scenario, we can find that simulation outputs of rice and soil loss are less varied than results of annual and perennial crops.

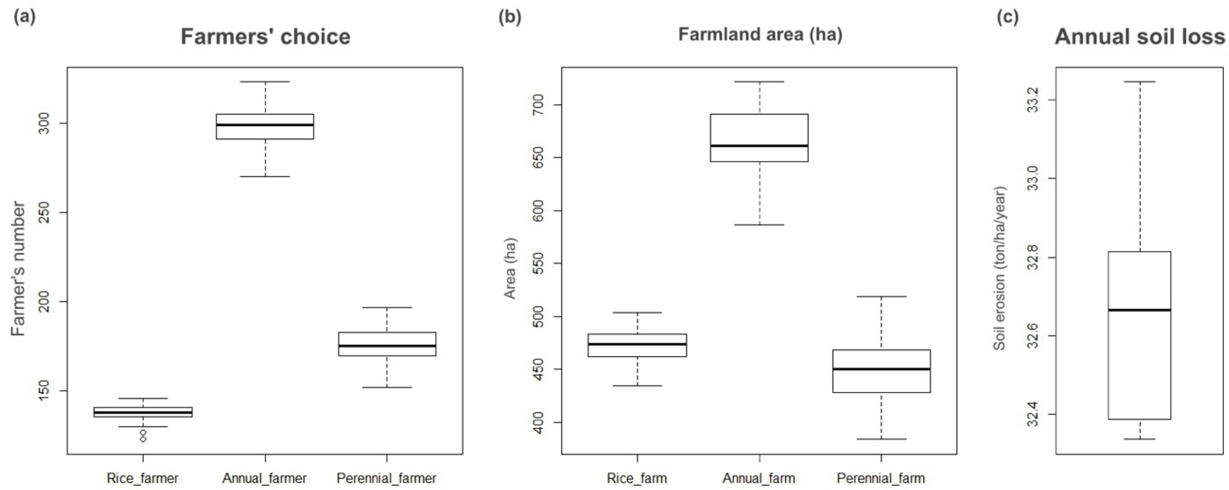

Figure 4. 4 Distribution of model outputs in the baseline scenario for uncertainty analysis: (a) is a distribution of farmer' numbers, (b) is a distribution of farmland areas, (c) is a distribution of annual soil erosion

To understand the explanatory powers of variables, we calculated ST indices for farmers' crop choice for each crop type of the model (Figure 4.5). For the rice crops, all variables have similar influences and spatial characteristics of the farmlands affect crop choices to a lower degree compared to annual and perennial crops because simulation outputs are less varied as shown in Figure 4.4 and thus single factor do not have strong influence on model outputs. As for annual crops, attitudes to ES (water quality and soil erosion) have the smallest influence on the model's output while topographic factors (elevation and slope) and neighborhood factors are most important for farmers' decisions with regards to annual crops. Decisions about perennial crops are influenced more by attitudes toward water quality while perennial farmers are less influenced by attitudes toward biomass production and perceived control factors (skill and knowledge and legal legislation). As for policy factors, rice farmers are more sensitive to subsidies while annual and perennial farmers are more sensitive to CBP. Among spatial features of farmlands, topographic factors (elevation and slope) are important while soil factors (organic carbon and bulk density) are less important for field crops. Neighboring crop status was extracted as a sensitive factor of crop choice in all crop decisions, which reflects the importance of spatial interactions of agricultural LUCC.

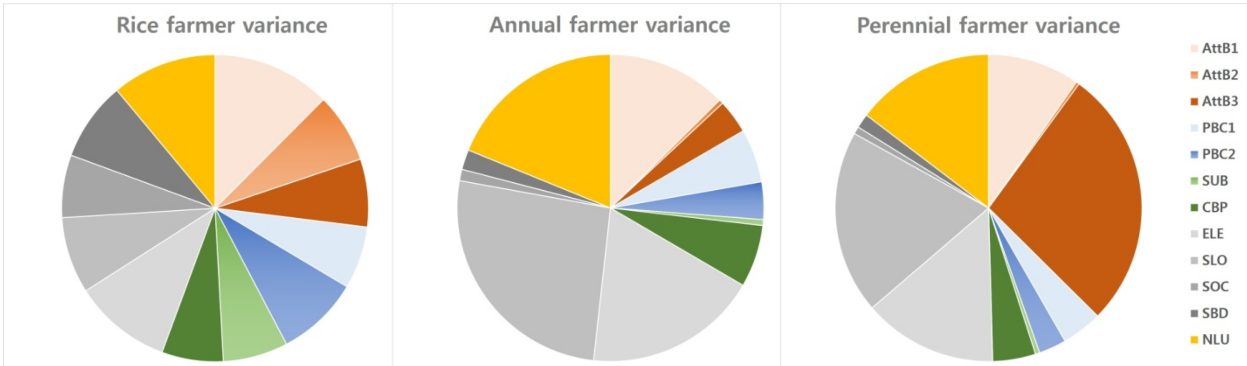

Figure 4. 5 Pie chart of ST (Total effect sensitivity) indices from sensitivity analysis for each output variable of crop choice (AttB1 = attitude toward biomass production, AttB2 = attitude toward soil loss reduction, AttB3 = attitude toward water quality improvement, PBC1 = skills and knowledge, PBC2 = legal legislation, SUB = subsidy, CBP = capacity building program, ELE = elevation, SLO = slope, SOC = soil organic carbon, SBD = soil bulk density, NLU = neighborhood land use %).

4.3.2 Scenario assessment

Our model simulated LUCC over the next 10 years under different scenarios (S1-3), compared to a baseline scenario (BAU) as shown in Figure 4.6-8. The simulation results indicate that common patterns are found in all scenarios, with rice and annual crops decreasing and perennial crops increasing, though change rates differ between scenario types. Another feature of the simulation results is different changes of farmers and their farmland, as the numbers of farmers adopting a given crop changes at a higher rate than the corresponding farmland area. Rice and annual crop farmers decrease more than rice farmlands in its' change rate while perennial farmers and farmlands show the opposite pattern. When we compare the BAU and S1 scenario, it is found that farm abandonments mainly occur in annual crop fields, while perennial farmers are less converted while rice and perennial crops have similar patterns between two scenarios (Figure 4.6 and 4.8). In the scenario, annual farms decrease by 170 ha while fallow lands increase by 130 ha as 7% of total agricultural areas. When we consider the S2 and S3 scenario for fallow land management, the ginseng farm expansion scenario (S3) is more effective in reducing soil erosion, which stably reduces annual soil loss. As for the S2 scenario, annual farms decrease with a higher variance than other scenarios although annual farmers decrease stably. In the S3 scenario, perennial crops increase higher than other scenarios while rice and annual crops decrease similarly with the S1 scenario, which reflects ginseng farm expansion by 180 ha as 109%. Because ginseng farms are expanded by outsiders, which is not considered in the ABM, perennial farmers increase less than farmland areas.

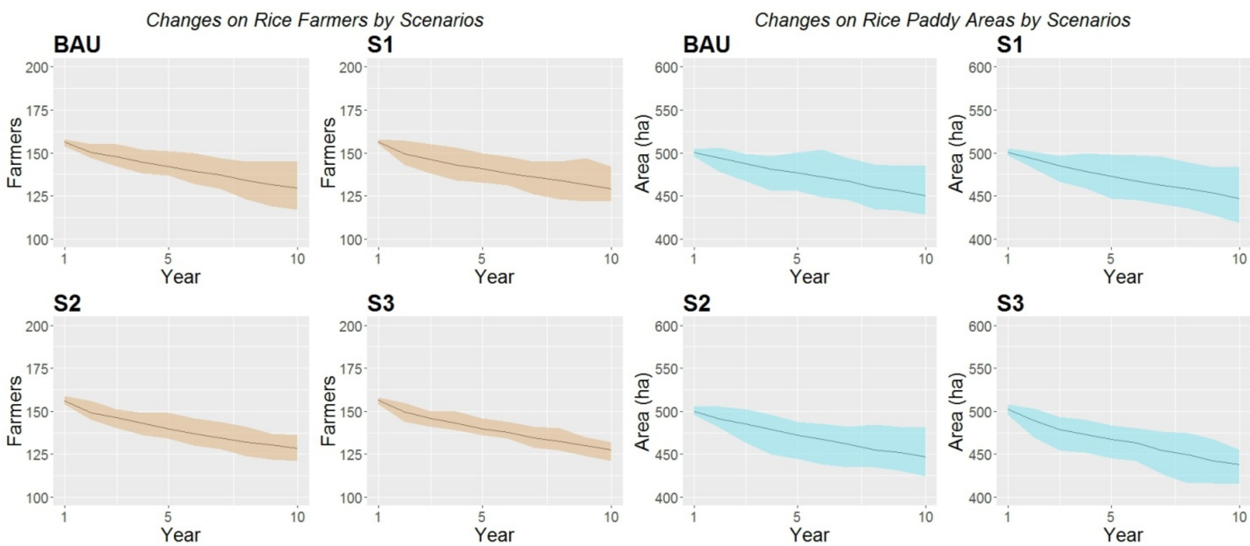

Figure 4. 6 Changes of a number of rice farmers (left) and their farm areas (right) by scenarios. BAU is a baseline, S1 is a fallow lands growth, S2 is a ginseng farm expansion, S3 is a perennial growth scenario.

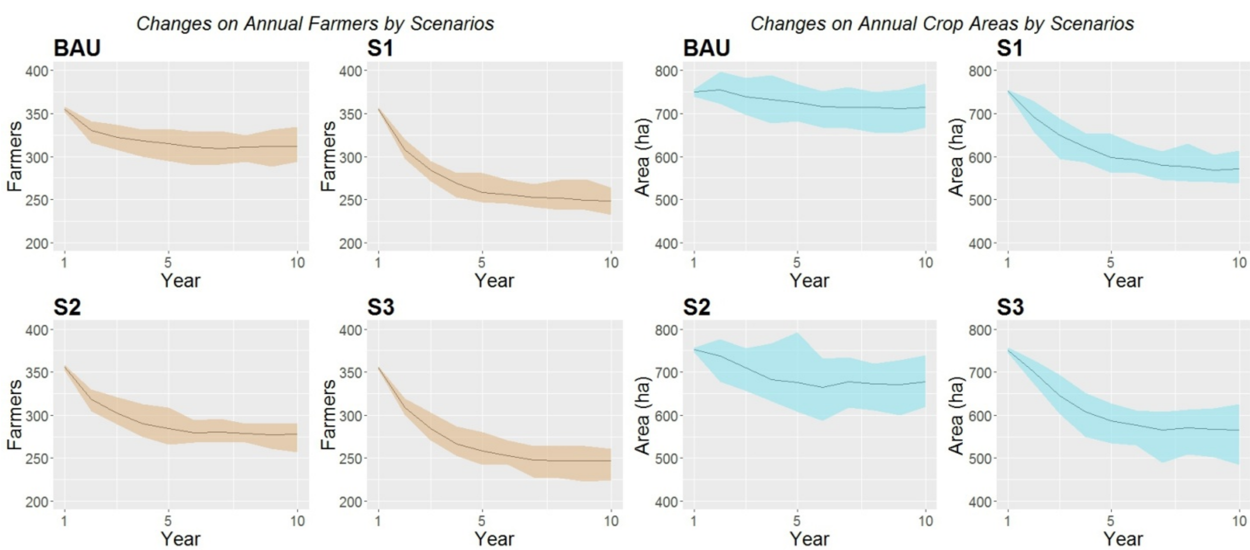

Figure 4. 7 Changes of a number of annual crop farmers (left) and their farm areas (right) by scenarios. BAU is a baseline, S1 is a fallow lands growth, S2 is a ginseng farm expansion, S3 is a perennial growth scenario.

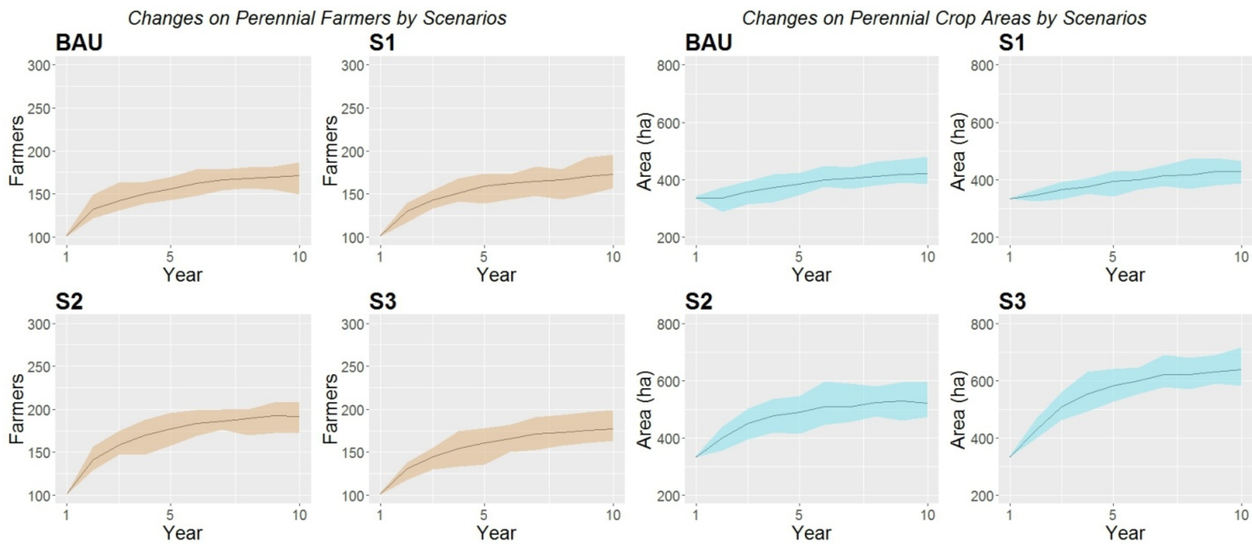

Figure 4. 8 Changes of a number of perennial crop farmers (left) and their farm areas (right) by scenarios. BAU is a baseline, S1 is a fallow lands growth, S2 is a ginseng farm expansion, S3 is a perennial growth scenario.

We also analyzed the impact of different agricultural land management scenarios on ES by estimating agricultural soil erosions loss (ton/ha/year) to assess ES. To estimate effects of agricultural LUCC, we simulated the RUSLE model to estimate soil erosion in the different scenarios. Soil erosion from agricultural LUCC changes little in the BAU scenario, which comes from different soil erosion rates of spatial features of farmlands (Figure 4.9). When considering the S1 scenarios, soil erosion rates increase by 6%, which is similar with in proportion to variability in fallow lands. To reduce soil erosion, we apply perennial and ginseng farm expansions, which cause reduction of annual soil loss compared to the S1 scenario. However, their effects on reduction of soil loss are less than expected, while perennial crop expansion decrease by 3% and ginseng farm expansion decrease by 6%.

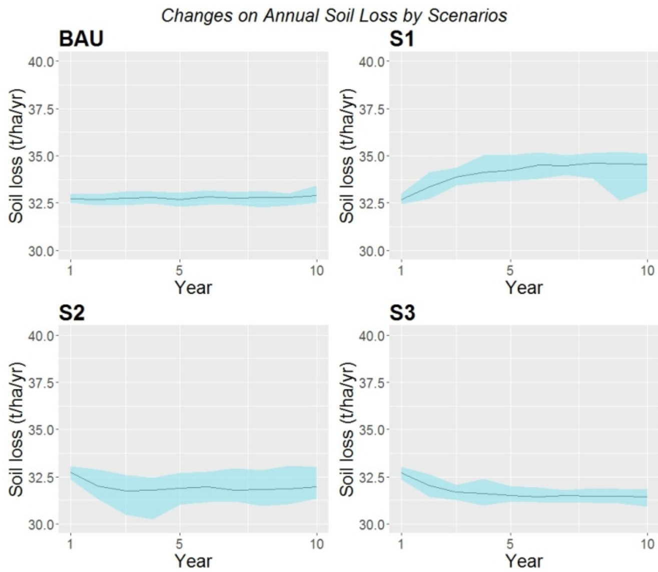

Figure 4. 9 Changes in annual soil erosion by scenario. BAU is a baseline, S1 is a fallow lands growth, S2 is a ginseng farm expansion, S3 is a perennial growth scenario.

4.4 Discussion

4.4.1 Crop choice and agricultural land use in the ABM

We developed an ABM of agricultural LUCC and crop choices based on farmers' attributes and spatial features of farmlands to simulate possible agricultural LUCC and its impacts on soil erosion. ABMs of agricultural LUCC have high levels of uncertainty due to limited information on agents and their decision-making process (Ligmann-Zielinska et al., 2014). Moreover, driving factors of crop choice extracted here are also different compared to those found in earlier research (Poppenborg and Koellner,2013), which did not consider spatial factors in MNL analysis. Therefore, we conducted uncertainty and sensitivity analyses to assess model outputs and inputs. Because output variables have diverse values due to different impacts of driving factors even in a single model (Ligmann-Zielinska et al., 2014), we estimated levels of uncertainty and sensitivity to estimate model performance. The model has different levels of variance of outputs depending on crop type and output factor while the rice model has a lower uncertainty than other crop types. This stems from features of rice paddies in rural areas, which are supported by the government for instance by direct payments. Additionally, older farmers tend to maintain their rice paddies because of suitable incomes and lower skills and knowledge (Jun and Kang, 2010), which also matches our results in Appendix

4.5. It is also found in the sensitivity analysis of the policy factors (subsidy and CBP) when rice is compared with other crops. Rice is comparatively more sensitive to subsidy and farmers' perception on legal legislation, unlike other crops. Annual and perennial crops, which change up to 10-15% annually (Table 4.1), have higher uncertainty of model outputs and their simulation results are interrelated with each other. Among farmers' perception factors, attitudes toward soil erosion and water quality have lower impacts on model outcomes while attitude on water quality has higher impacts than other perception factors, which is different compared with findings in other research (Poppenborg and Koellner, 2013).

4.4.2 Assessment of ecosystem services from ABM

The ABM simulates annual soil erosion rates from changes in agricultural area based on farmers' decision-making processes. From the simulation, we estimate possible changes in soil erosion at the watershed scale, which is linked to agricultural LUCC and related ES. Contrary to our expectations, soil erosion rate has low uncertainty. Mean values of annual soil erosion rates from all agricultural lands are estimated to be 32.7 ton/ha/year in the BAU scenario and 34.6 ton/ha/year in the S1 scenario. The value is less compared to earlier research (Poppenborg, 2014), which is estimated differently with regards to types of crops and management system (27-37 ton/ha/year). Our model includes fallow lands areas which cause severe soil loss than cultivated farmlands. Although the model could simulate agricultural LUCC and a typical ES in the research area, there are several challenges to developing a sophisticated modeling approach. In particular, quantification of soil erosion factors resulting from agricultural lands is a very significant reason to adopt RUSLE into LUCC simulation models due to uncertainty of the model and characteristics of land cover types. In the model, we adopt empirical results from Arnhold et al.(2014), who estimated regional specific C-factors according to crop type across the research site. Because C-factors differ by crop types, differences in soil erosion between crop choices have a lower impact unlike with simulation results from Poppenborg (2014). However, when we considered scenarios on fallow areas and ginseng farms without any empirical data in the region, values of C-factors could be problematic for estimating soil erosion. As for fallow lands, which varies from bare soils to natural vegetation cover. Panagos et al.(2015) estimated C-factors for specific land cover types from literature reviews, arriving at a 0.5 value for fallow lands. Because fallow lands have various forms from intermediate stages on bare soil to natural grasslands, we used median values between fallow lands and natural grasslands with 100% variance to reflect the uncertainty of model outputs. Although recent research reported that ginseng farms in the region could reduce soil erosion (Lee and Jeon, 2009; Jun and Kang, 2010), effects on ginseng farms are still problematic because most ginseng farms in the region do not have enough facilities to prevent soil erosion and caused severe soil erosion in the catchment (Cho, 2015). Because the effect of ginseng farms on reducing soil erosion on the research site is still uncertain, we set higher variation values on ginseng farms, which increased the uncertainty of the soil erosion results.

4.4.3 Policy implications on ES management

After the development of the model, we simulated farmers' agricultural LUCC and soil erosion under possible LUCC scenarios. Although the model simulates changes in agricultural land uses and ES by current status crop decisions, the results could help stakeholders to develop sustainable environmental and agricultural management plans. When we simulated scenarios (S1-S3), there was a possibility of a slight decrease in rice and annual crop farmers and increase in perennial farmers. However, spatial patterns of changes are different to the changes in farmers' status, which reflect smaller changes in farm area than farmers. This result could stem from features of farmers and their farm sizes. Rice farmers with larger farms have tendencies to change their farms to other crops, which explains the conversions from large rice farms due to lower income than field crops, while rice is cultivated by low-income and older farmers generating up to €750 per hectare for rice and €200 Euro per hectare for field crops. Highland farmers with capital strength and capacity increased their farmland size and adhered to annual crops (Kim, 2014). Annual crops are more sensitive to scenario changes, which could be related to farmers' intent in the region. Annual crop farmers have lower intent values than other farmers and could convert their crops when they have enough motivation to convert, such as economic and environmental factors. However, rice farmers are older than other farmers and have less capacity convert to other crops due to lack of information, skills and knowledge. Moreover, rice farmers receive stable government subsidies for cultivation in proportion to their farm size, which incentivizes them to cultivate rice as a stable source of income compared to field crops (Park and Seung, 2013).

The simulation results also indicate the importance of fallow land management, which generates higher soil erosion, for management plans. Many annual crop farms, called highland farms, are located on steep slope areas and are regarded as major water pollutant source. These areas have low suitability for cultivation and are easily converted to fallow lands when farmers have low capacity to change to other crops (Jun and Kang, 2010). Additionally, annual crops are sensitive to crop price changes due to market status and lower direct payment than rice, which resulted in increasing fallow land in dry field areas (Rhee et al., 2009). Fallow lands could increase by up to 85% in South Korea and cause ecocide and worsen agricultural conditions (Rhee et al., 2009). Our ABM can estimate possible changes in ES due to such changes in fallow lands. Ginseng farm expansions occur on fallow lands with lower LSI, whereas perennial farm expansion occurs where fallow lands have higher LSI, which are expected to reduce soil loss in the scenarios involving ginseng farm expansion. Although the magnitude of fallow lands decreases in the catchment, fallow lands in marginal forest areas with steep slopes remains as fallow lands, which causes severe soil loss than in other areas. Therefore, it is necessary to manage these marginal lands without agricultural activities such as reforestation policy, which focuses on conversion of these marginal lands to forest areas. From the simulation results, it turned out that ginseng farm expansions are more suitable for fallow land management plans, which generate less soil erosion than other crops because it stabilizes soils for cultivation periods of up to six years as Lee and Jeon (2009) estimated. In the ginseng expansion scenario, perennial farmland increased due to ginseng farm expansions, which are a typical type of perennial crop in the region. Although ginseng is mainly cultivated by outsiders in the region, who have less impact on farmers' interactions than local farmers in the network, changes in the regional landscape affect other farmers' decisions as indirect interactions, as explained in Figure 4.2. These changes in the environment lead to perennial expansions by local farmers who are affected by the land use status of neighboring land surrounding their farm areas.

4.4.4 Challenges to developing ABM integrated with ES models

We developed an ABM to simulate farmers' decision-making processes in an intensive agricultural area where severe soil erosion has occurred. To develop more sophisticated ABMs, several improvements are still possible. The first task is decision-making in fallow land conversions. We assumed that farmlands with lower LSI and lower farmer's intent values determine fallow land conversions in the region. To simulate them, we calculated LSI for agricultural practices and hypothesized that farmlands with lower LSI are easily converted to fallow lands, which reflect characteristics of farmers' land abandonment. Although LSI is useful to estimate agricultural capability and suitability, calculation of the values should be improved by combining field observation and stakeholder interviews because LSI could vary with regional characteristics and crop types (Reshmidevi et al., 2009; Liu et al., 2013). In particular, LSI values for rice paddies have different factors and thresholds to field crops in previous studies (Nguyen et al., 2015; Zhang et al., 2015) because there is a spatial difference of research areas enabling two or three-cultivation farming in rice in sub-tropical regions. These researches underestimate the effects of slope where bench terrace cropping is used. Rice farmers in South Korea, however, are more affected by spatial restraints like elevation and slopes, which affect the accessibility of labors and machinery to farmlands (Park and Kim, 2005). Although LSI has limitations, the value could imply various criteria for a decision on agricultural land management plans. Decision-making processes of land abandonment should be improved to reflect realistic changes of farmers' decisions. Most land abandonment progresses normally over a long period of time due to diverse factors (Brändle et al., 2015). However, fallow land in the catchment is occurs prepare ginseng farms in a short period as an intermediate stage of LUCC (Seo et al., 2014). To reflect realistic changes of regional LUCC, decision-making processes and scenario development of fallow and ginseng farm changes should be improved, although we already adopt a land abandonment decision-module by scenario types and estimate its impacts on soil erosion to comprehend possible changes.

The model has a limitation for the decision-making process of agricultural LUCC because it cannot consider economic factors due to limitations on farm households' economic data, such as agricultural costs and profits, as well as other income. Because of this limitation, we could not expand our model to combine agricultural policy and economic scenarios. We also cannot reflect land ownership in our ABM, although agricultural land use and fallow land transition in the region are strongly affected by land ownership status, which affects take-up of subsidies and direct payment (Jun and Kang, 2010). Although the model cannot reflect economic decision-making factors, it uses different spatial data to simulate possible agricultural changes where physical conditions are significant LUCC factors. We simulated changes in agricultural land management under different land use scenarios reflecting current characteristics of transitional periods of agricultural land use. The model also simulates farmers' direct and indirect communication, which could be converted to social opinion. i.e. social norms. Social interaction among farmers lead to the emergence of social norms and affect other farmers' opinions on agricultural land management plans (Chen et al., 2013).

4.5 Conclusion

The purpose of this study was to develop an ABM which capture various agricultural decision-making process and LUCC scenarios in the Haean catchment, where rapid agricultural LUCC as occurred, and their impacts on regional ecosystems. The model combines farmers' survey data on crop decision-making and fallow land conversions with spatial data reflecting physical constraints of agricultural activities. Farmers' decision regarding fallow land management are modeled based on spatial characteristics such as topography and soils, as well as farmers' intent, which reflects farmers' communications. The model focuses on spatial characteristics, farmers' perception and their social interactions, although there are limitations on modeling processes due to a lack of accessible data. From these results, we examined agricultural LUCC and related ES based on farmers' perceptions and spatial characteristic. Moreover, the model simulates possible changes in agricultural land use which could be a useful resource in policy making for environmental and agricultural management plans in the catchment.

4.6 Acknowledgement

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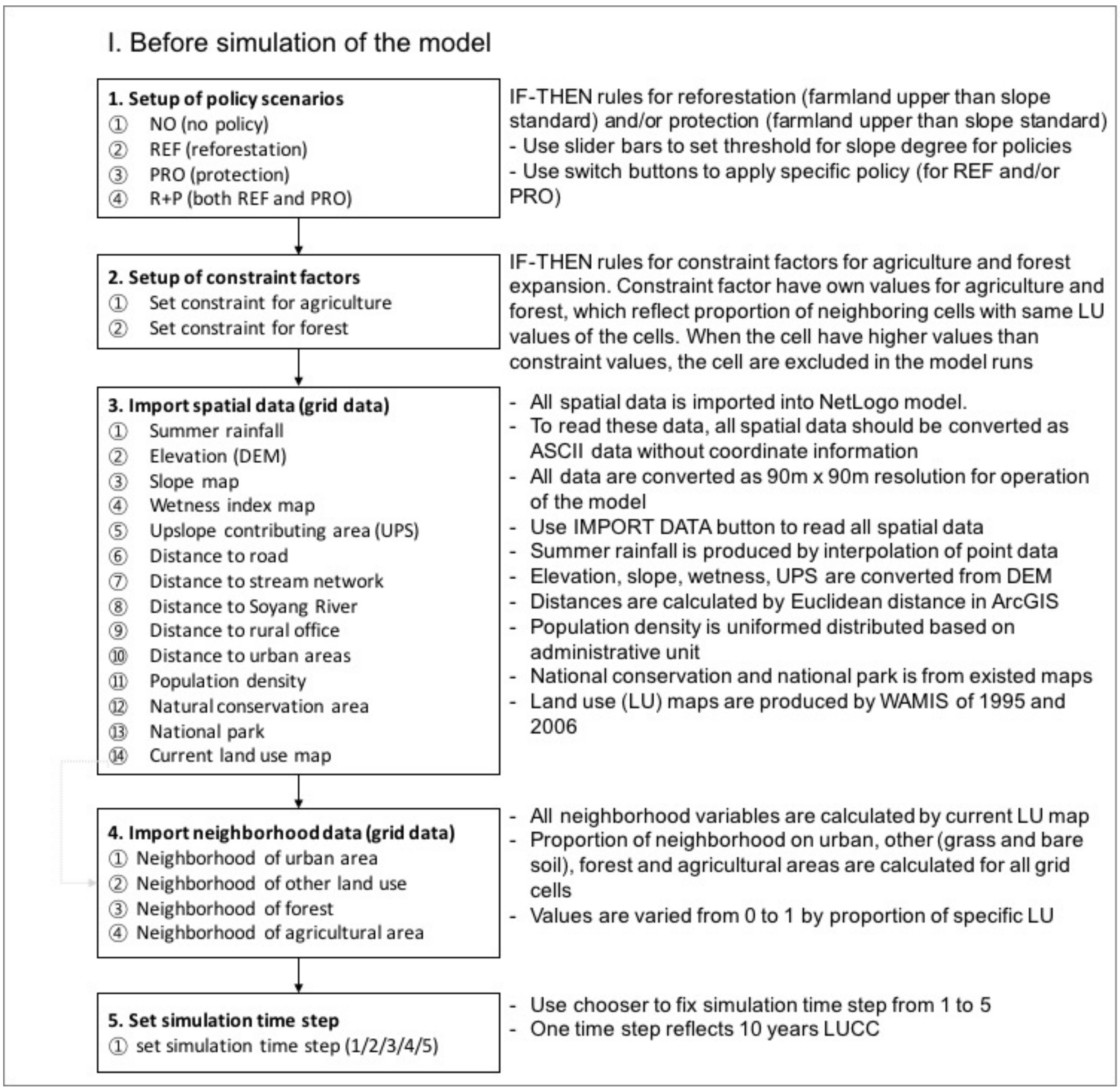
Appendix

Appendix 3.1. Process of CA model



II. Simulation process

1. Set time step (t + 1)

- Set time step for initial simulation
- Time step plus 1 when the next simulation start

2. Selection of cells for simulation

① Selection of cells based on constraint values
② Selection of forest cells based on protection policy
③ Random selection of agriculture cells up to policy adoption based on reforestation policy

- Grid cells for simulation of LUCC processes are selected
- If forest and agriculture cells are corresponded with constraint values, these cells are not selected in simulation
- IF forest cells are corresponded with target of protection policy, these cells are not selected in simulation
- IF agriculture cells are corresponded with target of reforestation policy once, these cells are not selected in simulation

3. Calculation of local transitional probability (TP)

① Calculate local TP of bare soil cells
② Calculate local TP of grassland cells
③ Calculate local TP of forest cells
④ Calculate local TP of rice paddy cells
⑤ Calculate local TP of dry field cells

- Calculate local transitional probability of cells
- Functions of transitional probability is based on expect value from MNL results (coefficient)
- For one cell, we can calculate TP for all possible changes
- In the model, we assume urban is not converted to other land types, so we do not calculate TB of urban cells, but other cells TB to urban is calculated

4. Calculation of TP combined with neighborhood proportion

① Calculate TP of bare soil cells
② Calculate TP of grassland cells
③ Calculate TP of forest cells
④ Calculate TP of rice paddy cells
⑤ Calculate TP of dry field cells

- Calculate overall transitional probability of cells
- Local TP is combined with neighborhood proportion to calculate TP from one LU to other LU
- Except all TP to other LU, it remains probability of no change

5. Predict land use change

① Predict LUCC of bare soil cells
② Predict LUCC of grassland cells
③ Predict LUCC of forest cells
④ Predict LUCC of rice paddy cells
⑤ Predict LUCC of dry field cells

- Based on their probability, section of specific change is decided (sample)

Urban	bare soil	Grass	Forest	Rice	Dryfield
0-0.2	0.2-0.3	0.3-0.4	0.4-0.6	0.6-0.8	0.8-1

- Generate random float number between 0 to 1
- When the value is apply in specific section, the grid cell is converted to specific LU where the section is located

6. Change status of cells

① Change cell values on land use
② Draw plots based on changes
③ Generate LU maps for this time step

- Change status of cells based on prediction result of cells
- Draw plots to visualize changes and generate graphs for temporal changes
- Generate LU maps for each time step for input of SWAT model

7. Update status of the cell and model

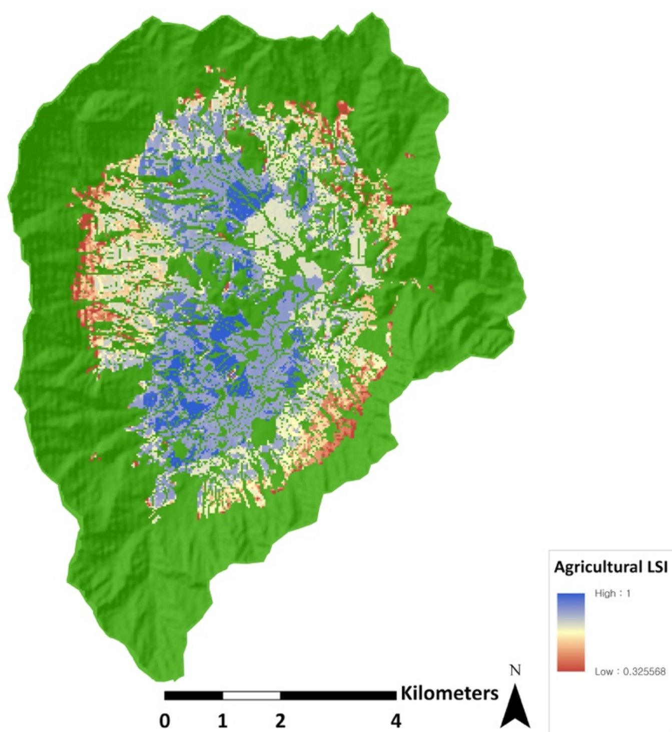
① Calculate constraint and neighborhood values based on update status of cells
② Calculate value of time step for loop

- Calculate updated constraint values of cells
- Calculate updated neighborhood values of cells
- Add 1 on time step (t = t + 1)
- Back to 1st step (set time step) until time step is matched with setting values

Appendix 4.1. Input factors and their fuzzy classification of agricultural suitability index (LSI)

Indicator	Type of function	Type of suitability class/level			
		S1	S2	S3	N
Slope (%)	S-shaped	x <=8	8 < x <=16	16 < x <=30	30 < x
Dist to road	S-shaped	X <= 500	500< x <=1000	1000 < x <= 2000	2000 < x
Organic carbon	Kendal	x >= 1	1 > x		
Soil texture	Class	Clay, sandy clay, sandy clay loam	Sandy loam	Loamy sand	Sand
Drainage class	Class	Good	Moderate	Imperfect	Poor

Appendix 4.2. Spatial distribution of agricultural land suitability index (LSI)



Appendix 4.3. Input factors and their values on RUSLE model

Factors	Values	Source
R-factor	6599.1 in whole catchment area	Arnhold et al., 2014[1]

K-factor	Calculated from soil maps	Lee et al, 2008[2]
LS-factor	Calculated from DEM	Lee et al, 2008
C-factor	Normally distributed with mean = 0.13, variance = 0.0013 for rice paddies; mean = 0.1417, variance = 0.0045 for annual crops; mean = 0.1257, variance = 0,0101 for perennial crops and ginseng farms; mean = 0.25, variance = 0.125 for fallow land	Lee et al., 2008; Arnold et al., 2014
P-factor	0.1 for rice paddies, 0.6-0.9 for annual crops, 0.6-0.9 for perennial crops and ginseng farms, 1 for fallow land	Lee et al, 2008

[1] Arnhold, S., Lindner, S., Lee, B., Martin, E., Kettering, J., Nguyen, T. T., Koellner, T., Ok, Y. S., Huwe, B., 2014. Conventional and organic farming: Soil erosion and conservation potential for row crop cultivation. Geoderma 219–220, 89–105.

[2] Lee, M. B., Kim, N. S., Jin, S., Kim, H. D., 2008. A Study on the soil erosion by landuse in the Imjin River Basin, DMZ of Central Korea. Journal of Korean Geographical Society 43(3), 263-275.

Appendix 4.4. Results of estimation on structures on social network model

Farmers type	Numbers of network / farmers	Mean Clustering coefficient	Mean Path length
Rice	4.79	0.225869	3.880547
Annual	3.62	0.179257	4.360535
Perennial	3.34	0.112857	5.065457

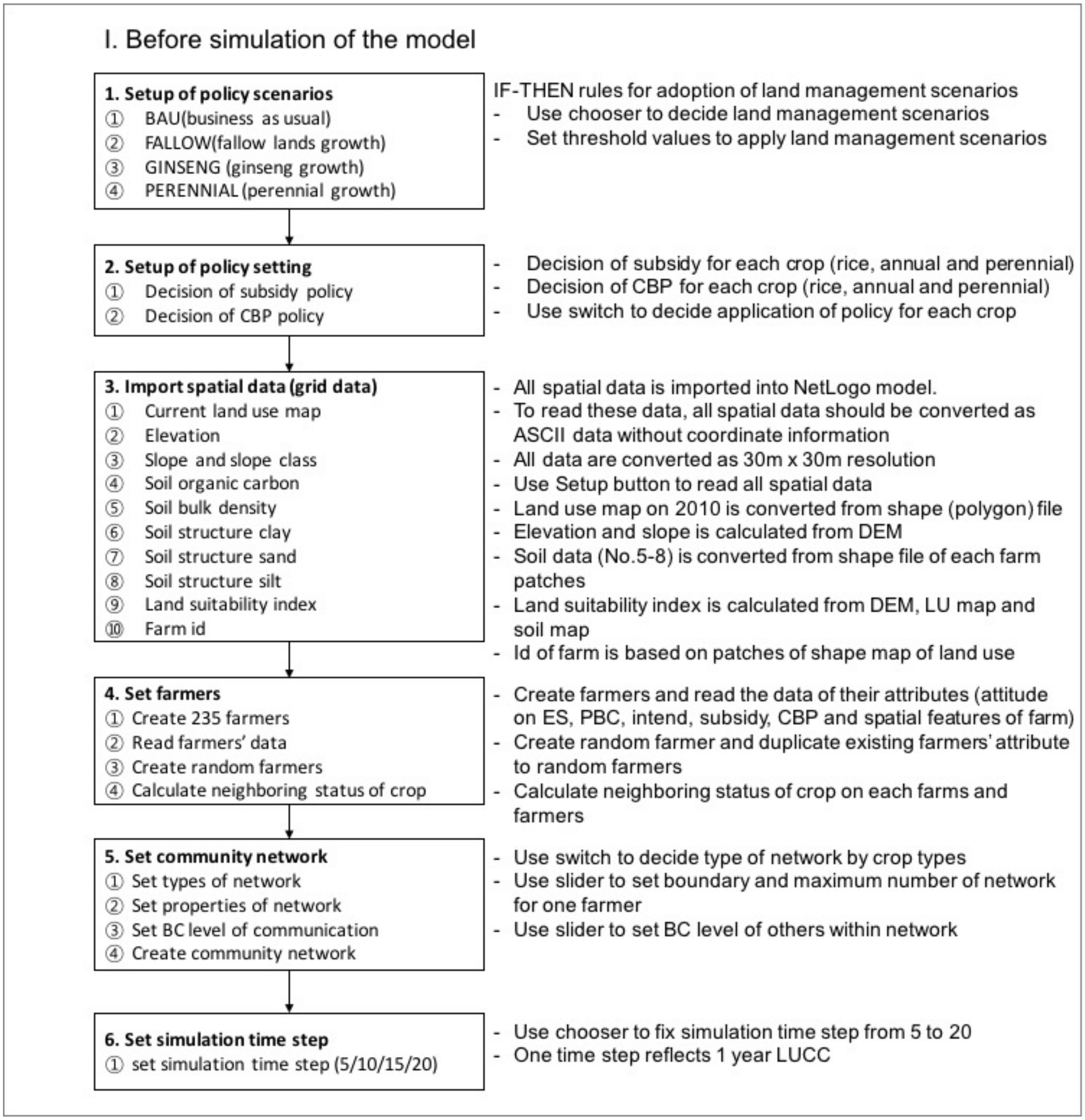
Appendix 4.5. Results of Multinomial Logistic Regression (MNL)

	Rice		**Annual crops**	
	β (std.err.)	Exp(β)	β (std.err.)	Exp(β)
Intercept	-27.854	-	-20.876	
Attitude toward behavior				
Biomass production	-0.271(0.072)**	0.762	-0.126(0.057)*	0.881
Soil loss reduction	0.104(0.215)	1.423	-0.021(0.053)	0.979
Water quality improvement	-0.007(0.234)	0.982	-0.106(0.056)	0.900
Perceived behavioral control				
Skills and knowledge	-0.278(0.261)**	0.757	-0.089(0.043)*	0.914
Legal legislation	0.128(0.054)*	1.137	.0.071(0.045)	1.074
Support				
[Subsidies = 1]	-1.362(0.604)	0.256	-0.008(0.684)	0.992
[Subsidies = 0]	0		0	
CBP				

[CBP=0]	0.940(0.927)	2.561	1.740(0.819)*	5.698
[CBP=0]	0		0	
Spatial characteristics				
Elevation (416 -673m)	-0.052(0.014)**	0.950	-0.026(0.010)*	0.974
Slope (0-22.7)	-0.336(0.162)*	0.715	-0.266(0.137)	0.767
Soil organic carbon (0.522-3.409)	1.743(2.235)	5.715	3.944(1.857)*	51.640
Soil bulk density (894.8-1281.46)	0.043(0.018)*	1.044	0.028(0.016)	1.028
Neighboring land use%	11.313(2.044)**	81879.821	5.645(1.741)**	282.975

(Cox and Snell $R^2 = 0.667$, $Chi^2 = 212.416$, **$p < 0.01$, *$p < 0.05$*)

Appendix 4.6. Process of ABM model



II. Simulation process

1. Set time step (t + 1)

- Set time step for initial simulation
- Time step plus 1 when the next simulation start

2. Calculate farmers' updated-intend

① Get other farmers' intend within their network with BC boundary
② Get mean values of their intent
③ Update farmers' intend

- Get connected-farmers' intent values with BC boundary (IF a gap between farmers' intend is higher than BC, this connection is not considered in this time step
- From mean intent of other farmers within network, farmers update their intend as updated-intend

3. Application of scenario

① Create random numbers
② Select dry field area lower than fallow threshold (LSI + farmers' intend)
③ Selection of farms to fallow lands
④ Selection of fallow lands to ginseng
⑤ Selection of fallow lands to perennial crops
⑥ Application of changes by types of scenarios

- Calculate fallow values (= farmer's intend on current crop + agricultural suitability of farmer's farm)
- Create random-float number to reflect uncertainty
- When fallow values is lower than threshold and random-float number exceed random threshold, convert farms to fallow
- When fallow values of fallow lands exceed threshold and random-float number exceed random threshold, farmers convert fallow lands to ginseng/perennial crops

4. Calculation of local transitional probability (TP)

① Calculate local TP of rice paddy cells
② Calculate local TP of annual crop cells
③ Calculate local TP of perennial crop cells

- Calculate local transitional probability of cells
- Functions of transitional probability is based on expect value from MNL results (coefficient)
- For one cell, we can calculate TP for all possible changes

5. Predict crop choice

① Apply weight values for actual LUCC
② Predict crop changes of rice paddies
③ Predict crop changes of annual crops
④ Predict crop changes of perennial crops

- This step is similar process is with prediction of CA model
- To reflect realistic changes I apply weight values based on actual LUCC from 2009 and 2010

6. Apply changes to cells

① Apply farmer' changes to farmland area
② Farmers change crop status of their own farms
③ Draw plots for crop choice and LUCC

- Change status of gird cells based on farmers' decision
- Draw plots in this step for update crop and LUCC status

7. Update status of farmers

① Update farmers' status on AttB and PBC
② Update farmers' status on crop intend
③ Update farmers' status on neighboring status

- Update farmers' status on Attitude on ES, PBC based on survey data and intend when they changes their crops
- Calculate new neighboring status of farmland

8. Calculate soil erosion

① Apply crop types as c- and p-factor of RUSLE
② C-factor is calculated by mean and SD of soil survey data
③ P-factor is calculated by crop status and slope degree of farmlands
④ Calculate RUSLE
⑤ Draw plots for soil erosion

- Calculate RUSLE based on LUCC
- C-factor is calculated in every time step based on mean and standard deviation values from soil survey data
- P-factor is calculated based on crop types and slope degrees of farmlands

(Eidesstattliche) Versicherungen und Erklärungen

(§ 8 S. 2 Nr. 6 PromO)

Hiermit erkläre ich mich damit einverstanden, dass die elektronische Fassung meiner Dissertation unter Wahrung meiner Urheberrechte und des Datenschutzes einer gesonderten Überprüfung hinsichtlich der eigenständigen Anfertigung der Dissertation unterzogen werden kann.

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Hiermit erkläre ich eidesstattlich, dass ich die Dissertation selbständig verfasst und keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt habe.

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Ich habe die Dissertation nicht bereits zur Erlangung eines akademischen Grades anderweitig eingereicht und habe auch nicht bereits diese oder eine gleichartige Doktorprüfung endgültig nicht bestanden.

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Ort, Datum, Unterschrift