Application of SWAT and Development of a Water Quality Predictive Model for Water Resources Management in Rural Basins

2020

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ACKNOWLEDGMENTS

The author expresses deep and sincere gratitude to Dr. Masayuki FUJIHARA, professor of Water Resources Engineering Laboratory, Division of Environmental Science and Technology, Graduate School of Agriculture, Kyoto University, and Chairperson of the examination committee for all the support, encouragement and valuable advice provided for improvement and completion of this research. The author would like to express special appreciation to Dr. Junichiro TAKEUCHI, Associate professor of Kyoto University, for serving as the project advisor and offering essential guidance and technical assistance during the entire research period. The author also expresses gratitude to Dr. Koichi UNAMI, Associate professor of Kyoto University, for all the advice and support provided.

Special regards are also extended to Dr. Akira MURAKAMI, professor and dean of the Graduate School of Agriculture and Dr. Kimihito NAKAMURA, professor of Kyoto University who served as members of the examination committee. Much appreciation also goes to all the students and secretaries who served in Water Resources Engineering Laboratory. They provided wonderful companionship, support, and important contribution to the progress of this research. The author also extends his gratitude to friends and family members for all their support and encouragement that served as an inspiration in the completion of this research.

The author would like to thank MEXT in a special way for their cordial support during the entire study period. The author is extremely thankful to Yasu River Land Improvement District, Shiga Prefectural Government, Kinki Regional Administration office, Ministry of Agriculture Forestry and Fisheries, and Water Quality Examination Laboratory, Kobe City Water Works Bureau for the provision of hydrological and water quality data.

CHAPTER 1

Introduction

1.1 Background

Water is essential for normal physical and cognitive functions of life. It is obtained from different natural and manmade sources. In the world, water bodies make up the largest natural resource. A higher percentage of this water resource is salty water with only 3% being freshwater (Jowsey, 2012). About 2 billion people in the current world depend on groundwater for their day to day activities. The other population of the world depends on water from surface bodies such as, lakes, rivers, ponds or streams, while others depend on rainwater.

The agricultural sector accounts for up to 70% of water consumed annually (FAO, 2015). Farmers use rainwater, surface water or groundwater in their farms for crop production, dairy farming as well as in aquatic farming. Water is also an important resource for domestic use. In our homes, water is used for drinking, cooking, cleaning, as well as recreational activities. Billions of liters of water are supplied to cities and urban areas to serve the ever growing urban population. Cities and most urban areas are mainly served with water from rivers and underground aquifers.

Industries and factories require water for their operation. Water is useful as a coolant where heavy machinery is involved. In other processes, water is part of the ingredient, especially in the foods and beverage industry. Other industrial use of water includes fabrication, diluting, product transporting, it is used in smelting facilities, industries producing, petroleum refineries, food and paper products. Water is also used in cleaning surfaces and equipment used in production. Water is also required in the building and construction industry for construction purposes where it is used for mixing. The building of houses and construction of roads requires a lot of water. In power, sector water is also important in production hydroelectric power (Jeppesen *et al.*, 2015).

Apart from water being used in the construction of roads, large water bodies are used for transport means. Water vessels are used to ferry cargo and passengers from one side of the water body to another. Water serves as a habitat for all aquatic animals. Both freshwater and saline water bodies play a host to millions of creatures. The ecosystem cannot balance without these creatures (Olmstead, 2014). In addition to conserving the ecosystem, sea life and other water bodies create beautiful sceneries which are an attraction to both local and international tourist, and this makes a major foreign income earner for different countries in the world.

1.2 Problem statement

Despite the numerous importance of water, there are several critical challenges facing water resources. As the human population increases, demand for water also increases across all sectors of life, causing depletion of water sources. At least 25% of big cities in the world are facing water scarcity (Olmstead, 2014). Water scarcity is a situation where the demand exceeds supply within specified boundaries. It is a global issue that affects up to 2.8 billion people (Jowsey, 2012). Water scarcity is characterized by water shortage, water stress, and water crisis. Increased human activities such as industrialization and agriculture, which are attributed mainly to the increased world population, have led to overexploitation of water resources.

Water scarcity is also attributed to climate change. Climate change is associated with temperature equilibrium on earth. Both negative and positive effects are experienced by human beings and the environment due to these changes. Global warming, for instance, causes energy imbalance by an increase in temperature which is brought about by an increase in greenhouse gas concentration in the atmosphere (Jeppesen *et al.*, 2015).

Most climatic changes in the world today are man-made and lead to direct and indirect consequences. Direct effects of climate change are increased ambient temperature, higher sea levels, and increased ocean temperatures, higher levels of precipitation, shrinking glaciers, and melting permafrost. The frequent occurrence of direct effects leads to the second wave of indirect impacts such as higher rates of water crises and hunger, health challenges that come with rising ambient temperature and from heatwaves, increase in pests and pathogens occurrence, economic setback experienced by countries when dealing with climate-related calamities, and an increase in greenhouse gases in the atmosphere leading to ocean acidification which in turn destroys aquatic life. Sectors such as forestry, agriculture, tourism, and infrastructure are forced to adapt to new climatic conditions, which in most cases, leads to compromised productivity that negatively affects water resources (Olmstead, 2014).

Water pollution is another factor that is accelerating water scarcity. Water is said to behave polluted if harmful substances such as chemicals and micro-organisms are deposited in water bodies. Water pollution lowers the quality of water by making it unsafe for human consumption and the environment. Water being a universal solvent is vulnerable to pollution due to its dissolving property (Ye *et al.*, 2013). Harmful substances from homes, farms, factories, and cities readily dissolve in water thus causing water pollution.

Agriculture ranks as the highest water resources pollutant. An increase in food demand has led to intensification of agriculture through activities such as irrigation, use of fertilizers, and pesticides. The increase in irrigation activities has led to the depletion of water from water bodies thus causing water deficiency for other sectors. Increased agricultural activities including deforestation leads to excessive soil erosion which pollutes water bodies. The runoff from agricultural fields is rich in excess phosphorous and nitrogen, and this causes bio-assimilation, eutrophication, growth of blue-green algae and hypoxia in water bodies thus affecting the quality of water (UNESCO, 2012). Nitrogen and phosphorus greatly affects aquatic life leading to extinction of some species. Some agrochemicals as pesticides and herbicides, are extremely toxic to humans and aquatic life. Wrong handling, selection, disposal and excess use of these pesticides and herbicides lead to accumulation in groundwater bodies making the water unfit for consumption (Ye *et al.*, 2013).

Industrialization also affects water resources. The growth in industries means a consequent increase in industrial effluents that in most cases find their way into rivers and other water bodies. If not well treated the wastes from industries negatively affects the quality of water leading to its deterioration. Oil is another dangerous hazard to water. Oil is lighter than water, therefore, it forms a layer on the water that prevents oxygen infiltration into water thus causing harm to aquatic life. Oil spillage can be from leaking oil tankers during transportation, or from industries, cars, and other machinery which use oil-based products (Lockwood *et al.*, 2010).

1.3 Importance of hydrological and water quality models

Water forms a part of the natural system. Such systems are hard to understand and manipulate without implementation of water quality and hydrological models. Water quality models focus on the behavior of a water pollutant from its source into water bodies. Due to mass kinetic activities and mass transfer, different concentrations are noted in the water bodies. Modeling is a time function that requires frequent advancements depending on the impending situation and available information (Schewe *et al.*, 2014).

Water quality models can help in identifying various pollutants in water bodies and developing well-calculated ways of ensuring that pollutants are minimized in water resources. They also have the task of identifying various factors leading to water resource depletion and coming up with models on how to overcome the challenge of overexploitation of the water resources (Schewe *et al.*, 2014). The models emulate real-life situation thus making it easier to come up with tangible recommendations and solutions.

Water quality modeling helps determine the number and amount of various contaminants and their sources. This makes it possible to control their effects. Increase in knowledge and technology has led to an increased number of water quality models. These models have the objective of measuring water quality, determining the behavior of various water impurities over time, and devising proper measures on how to maintain water quality (Kundzewicz and Stakhiv, 2010).

Hydrological modeling is mainly employed in running water within the storage basin. Through hydrological modeling, it is possible to conduct proper planning of the basin which enables proper policy implementation on proper management. It is also possible to identify the causes of runoff, and its effects on the environment (Schewe *et al.*, 2014). Through the models, it is possible to simulate the best method of controlling various aspects thus minimizing water body pollution. Models are useful in combining soil characteristics, characteristics of the catchment, land-use and climate conditions to determine their effects on water basins over time. Hydrological models help in the study of the effects of climate change and help people plan for impending climate change. With a proper recommendation, people can escape natural calamities such as flood hazards and prepare for drought by studying rainfall patterns to predict incidences (Moriasi *et al.*, 2015). Hydrological modeling help warn people of impending tragedies and this encourages them to conserve their environment.

Receiving water models predicts what happens to rivers, and lakes with an increase in pollutants and their effects on water bodies. Watershed loading modeling determines the contribution of each stage of runoff towards water body contamination. Through this information, it is possible to determine the areas which need consideration to improve the water quality and manage pollutants (Schewe *et al.*, 2014)

Hydrological models aid in water management which is very important in any community to conserve their water resources. Current and future water security depends on establishment of water management systems. A good water management system ensures there is a minimum waste of water with maximum utilization of available water (Moriasi *et al.*, 2015). A good management system also ensures that there are good water harvesting and storage strategies in place to ensure minimum wastage of this precious resource. Every government and state are making the advancement of reducing the problem of water scarcity through process modeling and forecasting (Ye *et al.*, 2013).

1.4 Objective

With changing environmental conditions and need for sustainability of water resources, hydrological and water quality establishment is necessary. For better policies on water management, there is a need for both present and past river quality and quantity status evaluation. Water quality management for instance, aims are answering the following questions: What is the present pollutant load? What is the present pollutant transfer? What are the effects of undermined water quality to the entire population in both present and future projections?

This study aims at applying hydrological and water quality modeling in rural basins where agriculture is the dominant human activity. Specific objectives include:

1. Hydrological simulation in a highly managed watershed where agriculture is the main land-use activity.
2. Developing a linear multiple prediction regression model for phosphorus load in the Sengari Reservoir basin.
3. Scenario testing on the effect of land cover change on phosphorus load in the Hatsuka River basin.
4. Estimation of non-point source phosphorus load in the Hazu River basin using a physical distributed model.

1.5 Thesis structure

The thesis is organized in seven chapters. Chapter 1 gives the general introduction which includes background, problem statement, importance of hydrological and water quality models, and objectives of the study.

Chapter 2 gives an extensive literature review for hydrological and water quality models. It focuses on the history of hydrological models, classification of models, physical based models, water quality models, and statistical/mathematical models.

Chapter 3 applies SWAT model in the Yasu River basin for long term simulation of daily discharge. The model applicability is tested based on agricultural activities and constructed reservoirs along the main channel.

Chapter 4 focuses on water quality modeling with linear regression model in the Sengari Reservoir basin. Phosphorus is the main pollutant under study. The model is developed based on the relationship between land-use and phosphorus load. Different land-use coefficients are developed from model useful for prediction of phosphorus load.

Chapter 5 evaluates the effect of land cover change on phosphorus load in the Hatsuka River basin. Non-point source phosphorus load is estimated from different sources. Several land cover change scenarios are evaluated and their effect on phosphorus load was quantified.

Chapter 6 applies SWAT model in the Hazu River basin. Here long term phosphorus load and discharge is simulated. The model is used for determining phosphorus load from different land-use and quantifying the effect of septic tanks in the basin after calibration and validation is conducted.

Chapter 7 gives the general summary and conclusion of the research as well as future prospects.

CHAPTER 2

Literature Review

2.1 Model introduction

A model is a simulation of a real-life process or system activities. A mimic of physical properties representing components of a natural system is the oldest form of models (Liu *et al.*, 2018). A model can be termed as a simplified representation of a complex system describing its basic and most important components (Xu, 2002). Hydrological models are developed to emulate the behavior of rainfall-runoff water. The simulation has a various block representing various stages from rainfall to creation of surface runoff and the effect that come about due to this runoff (Williams *et al.*, 2008). When water is on the surface various processes take place: the water can form a stream and flow towards the river, evaporate from the surface when the temperature is high, and infiltrate into the soil when the drainage is favorable.

2.2 History of hydrological models and water quality models

The origin of hydrological modeling can be traced back with the concept of rational method of determining flood peak discharge from measurement of rainfall depth (Mulvany, 1850) . Another historical study was an event modeling relating storm runoff peak to rainfall intensity (Imbeau, 1892). Other significant studies that served as benchmark for hydrological modeling include the development of unit hydrograph concept (Sherman, 1932), infiltration theory (Horton, 1933) and theory of evaporation (Penman, 1948; Singh and Woolhiser, 2002)

The main idea behind these early models was the theoretical and conceptual representation of various hydrologic components in the hydrological cycle. At first, they were entirely mathematical models that gained physical qualities with time. Different components in the hydrological cycle worked separately until the 1960s when computing was introduced and enabled the components to work as a single unit (Gassman *et al.*, 2007). The development of the Hydrologic Simulation Program-Fortran (HSPF) (Johanson *et al*., 1984), model after the computation era led to the development of watershed models. In the beginning, the models were simple but with time the models have grown in complexity due to increased computation power. Modern models have the capacity of including several physical processes in a single program simulation. Current models are able to incorporate time-variant physical parameters (Seitzinger *et al.*, 2005), and have the capacity of responding to real-time data to represent time-variant scenarios (Williams *et al.*, 2008).

2.3 Different groups of hydrological models

An elaborate compilation of different classifications by Xu (2002) places hydrological models in different categories as follows, (1) Material models/physical models: A model is termed material/physical when a real system is represented by an alternative system with similar properties and much easier to work with. Material models are further classified as iconic, scale and analog models. (2) Formal/symbolic/abstract models: logical terms are expressed symbolically based on idealized and simple situation with structural properties of the original system. Mathematical models are typical examples which express behavior of a system by sets of equations. (3) Theoretical models/white-box models/physically based models: They are formed by important laws governing a phenomenon. It is represented by a logical structure resembling the real-world system. (4) Empirical models/black-box models/input output models: They do not focus on the physical understanding of the system as they contain little physical significance. They are estimated based on concurrent measurement of input and output. Stochastic time series models serve as an example. (5) Conceptual models/grey-box models: They lie between theoretical and empirical models such that a functional equation considers the physical processes acting on the input variables to produce the output variables. They take into account highly simplified physical laws. Models whether theoretical, conceptual or empirical may be linear or non-linear. (6) Lumped models: The entire basin is assumed to be homogenous through semi-distributed models. Flow from different subbasins are considered homogenous within themselves. (7) Distributed models: Here elementary unit area like grid nets divides the entire basin. As water drains through the basin, flows move from one grid point to another. (8) Stochastic models: It is considered when any of the variables are random with distribution probability. (9) Deterministic models: When all variables are free from variation and one having a distribution probability. (10) Time-invariant models: Relationship between input and output in this model does not change with time. (11) Time-variant models: Relationship between input and output in the model changes with time.

2.4 Physical based models

As the name suggests these modes employ physical properties such as amount of rainfall, topography of the location, soil type in the watershed, soil depth, amount of ground cover and water infiltration, evaporation, and evapotranspiration coefficient in model computation (Arnold *et al.*, 2012). Physical models are aimed at determining the occurrence, movement, distribution and storage of water in a time space variant model. Physical based models are generally complex in nature. To simplify these processes various sections and processes can be lumped together in a given space and time period. They use physical theories such as conservation of mass and conservation of momentum to govern various processes (Arnold *et al.*, 2012). They are important because they create useful tools in understanding various hydrologic phenomenon taking place in a watershed and how various physical conditions on the watershed affect these phenomena. Physical based models utilized both continuity equation, energy equation and momentum equation. The number of equations used determine the complexity of the model.

The main area of components in physical based models includes rainfall occurrence, water runoff, distribution of rainfall and runoffs, water storage capacity of the soil, and vegetation present. The models will try to give the variation of these properties for a specific location over time. Physical based models employ several technologies in their modeling. We have hydrodynamic models that use both physical and theoretical functioning of a hydraulic model. Use of momentum and continuity equations are also essential especially in overland and channel flows. The modeling process might choose to employ 1D, 2D or 3D models depending on the availability of software and data required, despite the natural phenomena being a 3D (Arnold *et al.*, 2012).

Simulation models employ mathematical equation to determine results such as runoff capacity, or peak flow while computer models use numerical and logical methods to compute a time-space variant behavior of the system. Through numerical simulation models it is possible to mimic complex rain intensities and patterns to come up with heterogeneous watershed models. From the results, it is possible to enforce policies that ensure proper land-use and ground cover determination. Spatial characteristics improves the results obtained from the modeling process. Study on the blue print of a physically based digitally simulated hydrographic model (Freeze and Harlan, 1969) formed the pioneering outline of distributed physically based model (Refsgaard, 1997). Since then numerous distributed physically based models have been developed. Examples of physical based models in water resources management are SWAT (Arnold *et al*., 1998), SHE (Abbott *et al*., 1986), TOPMODEL (Beven and Kirkby, 1979), among others.

The most notable strengths of the physical based watershed models are that, they are readily obtainable and can be used by managers in modeling the quantity and quality of different water resources across the world. They also tend to incorporate the condition of land and waterway environmental processes. Simulation is carried out on an hourly basis, day to day basis, once-a-month or even on an annually basis over a period of many years (Arnold *et al.*, 2012). Most of these models have an easily applicable platform that accepts simulations of agricultural and environmental conditions incorporation with the most ideal crop and land management practices. The tools also allow incorporation of different agricultural practices such as crop rotation, application of fertilizer, timely planting and harvesting, type of water application among other activities, and the incorporation of these scenarios greatly impact the accurateness of the findings.

2.5 Distributed and semi-distributed models

In distributed models, chosen parameters are allowed to vary according to a real-life situation as directed by the user. Both spatial parameter distribution and computation algorithms are employed in modeling various behaviors of a watershed (Khakbaz *et al.*, 2012). The output is a factor of various input parameters: the amount of rainfall, the amount of crop cover, the type of soil present, and the complexity of the computational power of the model selected. Large amounts of data are required for adequate simulation of a time-variant situation. It requires a wide knowledge of the physical properties examined since the modeling process is more detailed than the previous groups (El-Nasr *et al.*, 2005). Due to the detailed approach, it is possible to obtain results from any point in a watershed and at any time. Distributed models provide more accurate results since rainfall and runoff water can be simulated to represent a real scenario. Some of the disadvantages associated with distributed models include: more time is required in the computation and model programming stage, due to intensive physical properties consideration, it requires experts thus making these models more expensive to implement (El-Nasr *et al.*, 2005). Various mass and momentum equations are employed.

For semi-distributed model, a watershed is divided into subbasins and the parameters allow to vary partially from one subbasin to another. They can be divided into probability distributed model such as SWMM, TOPMODEL, and SWAT, or kinematic wave theory model such as the HEC-HMS (Khakbaz *et al.*, 2012). In probability distributed models the contribution from each subbasin is accounted for by the use of probability distribution equation. The output from this model depends more on physical parameters unlike in the case of lumped models. Subbasin estimated are collected at various creek points and through probability distribution, the nature of the entire watershed can be determined from the model (Khakbaz *et al.*, 2012).

2.6 Water quality models

Water quality model is a simulation model that can be used to predict the level, and the distribution of various pollutant on water body surface. Different pollution prototypes are employed depending on the sources of pollution to come up with different models. From the models it is possible to determine where the water body is still safe for human and aquatic life. For a model to be effective base/standards are set depending on the targeted use of water (Bartley *et al.*, 2012).

The first water quality model was used in the state of Ohio. The model referred to as S-P was developed by Streeter and Phelps (1925). Operation of this model was affected by a single factor. Current models have increased in complexity and now have the capacity of incorporating multiple water quality factors (Kannel *et al.,* 2011). Evolution is not the only the number of factors based but also; from steady state to dynamic model, from no dimensional models to multi-dimensional models. We also have an advancement from the point source model to the coupling model and later development of non-point models. Several water quality models are in the market at the moment (Bartley *et al.*, 2012). Examples of models utilized for simulating watershed-scale pollutant transport include SWAT (Arnold *et al*., 1998), Hydrologic Simulation Program- Fortran (HSPF) (Johanson *et al*., 1984), Areal Non-point Source Watershed Environment Response Simulation-2000 (ANSWERS) (Beasley *et al*., 1985), MIKESHE (Danish Hydraulic Institute, 2007), Agricultural Runoff Model (ARM) (Donigian *et al*., 1977), Watershed Analysis Risk Management Framework (WARMF) (Chen *et al*., 1999), Erosion Productivity Impact Calculator (EPIC) (Sharpley and Williams, 1990), among others.

These models are classified according to type of water body to be modeled, the method used to develop the model, water quality standard, water quality parameters, model properties, latitudinal dimensions, and reaction dynamics. All water models have their merits and demerits therefore it is important to select a suitable model to employ based on your study parameters. More studies on how to minimize limitations are also needed to improve the viability of these models (Tsakiris and Alexakis, 2012).

Water quality models are categorized into spatially explicit statistical models such as LCD (Stiles, 2001), SELECT (Teague *et al*., 2009) and SPARROW (USGS, 2006); mass balance such as BLEST (Petersen *et al*., 2009); and mechanistic hydrologic water quality models including HSPF, SWAT, SWMM, and WASP (US EPA, 1983). These models range from simple to very complex. Each model is useful in ensuring water quality is maintained through policy, proper actions and implementation (Ward *et al*., 2009).

Statistical water quality models are aimed at estimating the number of activities contributing to pollutants downstream. Some of the factors to consider in a deterministic model include the hydrology of the area, the weather conditions of the area, sedimentation rates, crop cover, soil nutrients, pesticide application, groundwater lateral flow, management scenarios, and bacteria presence (Ward *et al*., 2009).

Advancements in technology and the ability of mathematical theories to represent various physical properties mathematically has led to the increased developments in water quality models over the years. More models have been developed with hundreds of software that have proven useful. Different models are used based on topography, size of water bodies and nature of pollutants (Ernst and Owens, 2009).

2.7 Examples of water quality models

WASP (Water Quality Analysis Simulation Program) model was developed by the US Environmental Protection Agency (1983).The model is applicable in lakes, rivers, reservoirs, and coastal wet land model simulation (Ernst and Owens, 2009). Model implementation can be either 1D, 2D or 3D model. This model was used in sensitivity analysis, nutrient simulation, dissolve oxygen and chlorophyll dynamics in the Shenandoah River watershed (Lindenschmidt, 2006).

EFDC (Environmental Fluid Dynamics Code) water quality model was conceptualized at the Virginia institute of marine science and approved US EPA (Bai and Lung, 2005). It was first used in 1997. It can be applied in lakes, reservoirs, estuaries, rivers, and wetlands water quality modeling. It can be implemented in 1D, 2D, or 3D model. The model employs the following equations: hydrostatic equation of momentum, fluid flow equation, states equation, transport equation, and second moment turbulence equation (Liu *et al.*, 2007). The application of EFDC in a series for water quality modeling of the Yongdam Lake, Korea is one of the examples in which EFDC was used in the study of water quality (Seo and Kim, 2011).

QUASAR model was established by Whitehead (1997). Its application is mainly in determining the amount of dissolved oxygen in water. The model is a 1D dynamic model. BASIN water quality model was developed in the year 1996 by the US Environmental

Protection Agency (Wang *et al.*, 2013). The basin models were mainly developed to deal with multipurpose environmental analysis systems. Their applications are in watershed water quality determination and monitoring.

QUAL I, QUAL II, QUAL 2E, QUAL 2E UNCAS and QUAL 2K water quality models, were also developed by the US environmental protection agency in the year 1970. They are mainly employed in dendritic river and non-point source pollution. Most of this model are 1D steady-state or 1D dynamic models (Paliwal *et al*., 2007; Wang *et al.*, 2013).

MIKE models constitute of the following versions: MIKE 11, MIKE 21, and MIKE 31. They were developed by the Denmark Hydrology Institute. With the model it is possible to simulate water quality in estuaries, rivers, and tidal wetlands. The models can be either 1D, 2D, or 3D (Tsakiris and Alexakis, 2012; Wang *et al.*, 2013).

2.8 SWAT model

Soil Water Assessment Tool (SWAT) is a physically based watershed scale model that requires information on weather, soil properties, topography, vegetation, and land management practice in the watershed. It was developed to predict the impact of land management practice on water sediments and agricultural chemical yields (Neitsch *et al*., 2011). SWAT model is equipped with various components as hydrology, weather, erosion, soil, temperature, crop growth, nutrients, pesticides, and agricultural management practice (Neitsch *et al*., 2005). SWAT was developed from SWRRB (Simulator for Water Resources in Rural Basins) model (Arnold *et al.*, 1990). Other models that played an important role in the development of SWAT model included CREAMS (Chemical, Runoff and Erosion from Agricultural Management Systems) (Kinsel, 1980), GLEAMS (Groundwater Loading Effect on Agricultural Management Systems) (Leonard *et al*., 1987) and EPIC (Erosion- Productivity Impact Calculator) (Williams *et al*., 1984).

The watershed is divided into subbasins where the inputs are categorized as climate, hydrological response unit (HRU), wetlands, groundwater, and the main channel draining into the subbasin. HRU is a combination of unique land cover, soil and management practice. Hydrological part in SWAT model is equipped to simulate evapotranspiration, snowmelt, surface runoff, infiltration, percolation, return flow, groundwater flow, channel transmission loss, pond and reservoir storage, channel routing, tile drainage, and plant water use process (Arnold *et al*., 1999).

Land and routing phase hydraulic cycle forms the basis of watershed hydrology simulation. Amount of water, sediments, and nutrients and pesticide loading to the main channel in each subbasin are controlled by land phase hydraulic cycle while routing phase entails loading through the channel network to the outlet. Surface runoff is simulated by modified Soil Conservation Service (SCS) curve number method (USGS, 1972) and Green-Ampt infiltration method (Green and Ampt, 1911). Peak runoff rate is simulated using modified rational method. Surface runoff is calculated as the difference between precipitation and the amount of water infiltrating the soil.

When water is applied on the soil surface, there is continuous movement of water through the soil profile known as redistribution. It is attributed to the difference in water content through the soil profile. Lateral flow which contributes to streamflow is computed simultaneously with redistribution. Groundwater in the model is partitioned into shallow unconfined aquifer and deep confined aquifer. Unconfined aquifer adds return flow into the stream within the watershed. Transmission loss due to leaching through the streambed is estimated by Lanes method (USGS, 1972). Evaporation loss is computed from both soil and plants based on the potential evapotranspiration (Ritchie, 1972). Three methods are used to estimate potential evapotranspiration. These include Hargreves (Hargreaves *et al.*, 1985), Priestely Taylor (Priestley and Taylor, 1972) and Penman Monteith (Monteith, 1965) methods.

SWAT model characterized as process based, computationally efficient, and capable of continuous simulation over long time periods (Neitsch *et al*., 2011; Abbaspour *et al*., 2015) has been applied in different parts of the world. In Japan for instance, the model has been used for sensitivity analyses of hydrologic and suspended sediment discharge (Somura *et al*., 2009), analyzing effect of climate change on nutrient discharge (Shimizu *et al*., 2011), calibration and uncertainty analysis (Luo *et al*., 2011), impact of suspended elements on nutrient loading from land-uses against water quality (Somura *et al*., 2012), simulation of nutrients from an agricultural watershed (Kato *et al*., 2011), modeling water balance processes for understanding the components of river discharge (Jiang *et al*., 2011), dam construction impacts on stream flow and nutrient transport (Supit and Ohgushi, 2012), simulation of stream nitrate-nitrogen export (Jiang *et al*., 2014), water yield, nitrogen and sediment retentions (Fan and Shibata, 2016), examination of the water balance of irrigated paddy fields (Sakaguchi *et al*., 2014) , estimation of phosphorus discharge in a suburban catchment (Shimizu *et al.*, 2013), among other studies. Varying agro-climatic conditions in different areas and their unique characteristics raises the need to conduct hydrological models in different watersheds (Uniyal *et al*., 2015).

CHAPTER 3

Applicability of SWAT Model for Streamflow Simulation in a Highly Managed Agricultural Watershed

3.1 Introduction

Water is a natural renewable resource vital for human survival. All aspects of society and development are supported by fresh water and inland water bodies. Water cycle plays a key role in ecosystem health, and supports basic human needs and cultural uses. Water use cuts across municipal, industrial, agricultural and energy sectors. Increasing population and subsequent demand for resources to improve living standards among other external forces are increasing pressure on local and regional water supplies for irrigation, energy production, industrial and domestic purposes. Addressing these challenges has been hindered by lack of comprehensive understanding of hydraulic and climatic system. They not only behave in a non-linear manner but also their interaction is complex as well (Gourbesville, 2008). A highly managed watershed is characterized by intensive human activities and natural processes play a secondary role. Management activities include dam construction, reservoirs, water transfer, irrigation among other activities that disrupt the natural movement of water (Abbaspour, 2015).

One of the fundamental requirements in water resource assessment, development and management is watershed modeling. It is utilized in various ways as analyzing the quality and quantity of streamflow, reservoir system operations, groundwater development and protection, water distribution system, and water use among other management activities (Singh and Woolhiser, 2002; Wurbs, 1998). Dynamic interactions of climate and surface hydrology as well as the impact of climate change on water resources and agricultural productivity are achieved through watershed models. For environmental and water resource protection, impact of watershed management strategies associating human activities with quality and quantity of water within the watershed is also conducted through the models (Singh and Woolhiser, 2002; Mankin *et al*., 1999; Rudra *et al*., 1999).

With evolvement of hydrological models over time, dynamic distributed models are increasingly being applied to address different needs in water resources management (Uniyal *et al*., 2015). They provide a comprehensive description of the catchment topography, computation of surface water depth, flow discharge and variation in space of infiltration and precipitation (Fernández-Pato *et al.*, 2016). However due to complexity in natural systems, hydrological models are bound to different uncertainties which should be quantified to capture our level of ignorance. Uncertainty varies from conceptual, input and parameter uncertainties. Conceptual uncertainties are due to simplification of the conceptual model, process occurring in the watershed but not included in the model, process included in the model but their occurrence is unknown to the modeler, and process unknown to the modeler and not included in the model. Input uncertainty is attributed to error in input data and parameter uncertainty is due to inherent non-uniqueness of parameter in inverse modeling (Abbaspour, 2015). Modeling procedure requires, transparent description, calibration, validation and sensitivity and uncertainty analysis performed (Abbaspour *et al.,* 2015).

Among different hydrological models already developed, Soil Water Assessment Tool (SWAT) is one of the most used. The model being process based, computationally efficient, and capable of continuous simulation over long time periods (Neitsch *et al*., 2011), has been applied in different parts of the world. The main objective of this study is to apply SWAT model for long term streamflow simulation in the Yasu River basin characterized as highly managed due to human activities as agriculture dominated by irrigation and artificial reservoirs along the main channel. Sequential Uncertainty Fitting Algorithm (SUFI-2) is used as the optimization techniques for model calibration, validation sensitivity and uncertainty analysis.

3.2 Methodology

3.2.1 Study area

The Yasu River basin is located in the Honshu Island Japan and lies between coordinates N 34°51' to 35°07' and E 135°58' to 136°26'. It originates from Mount Gozaisho and drains into Lake Biwa. The basin has a catchment area of 387 km² with a total length of 65 km from the source to mouth. The watershed has undulating topography ranging from 97 m to 1,234 m above sea level. Four climatic seasons of summer, autumn, winter, and spring are experienced around the year. The basin receives high amount of rainfall with a mean of about 1,587 mm per annum. The location of the study area is shown in Figure 3.1.

Spatial datasets includes Digital Elevation Model (DEM), land-use and soil data obtained from Shiga Prefecture. Figure 3.2 shows spatial elevation in the Yasu River basin. DEM has a spatial resolution of 30m by 30m. It is used for watershed and subbasin delineation covering the entire process of flow direction, flow accumulation, and stream network generation. Figure 3.3 shows the spatial distribution of land-use in the basin. The dominant land cover in the basin is forest occupying 61% of the area. Paddy fields occupy 18% of the land. Settlements, upland field, golf course, water and other land occupy 21% of the area.

Figure 3.4 shows the spatial distribution of soil in the basin. Soil distribution is dominated by brown forest soil covering (BFS) an extent of 39% of the land because a large area is under forest cover. 21% of soil data is unclassified (UNC). Immature soil (IMS) occupies 18% of the land with gley lowland soil (GLS) covering 13%. Gley soil (GS), yellow soil (YES), red soil (RDS) and andasol (AND) combined covers 9% of the land. Soil dataset serves as an input in SWAT model for formation of HRUs in the basin.

Temporal datasets comprise of climatic and hydrological data from the year 1990 to 2009. Location of hydraulic structures and weather stations are shown in Figure 3.5. Climate data includes precipitation, temperature, humidity, wind, and solar radiation. Four stations serve as the source of climatic data: Higashiomi, Otsu, Shigaraki, and Tsuchiyama. Hydrological data includes daily streamflow from the Yasu gauging station,

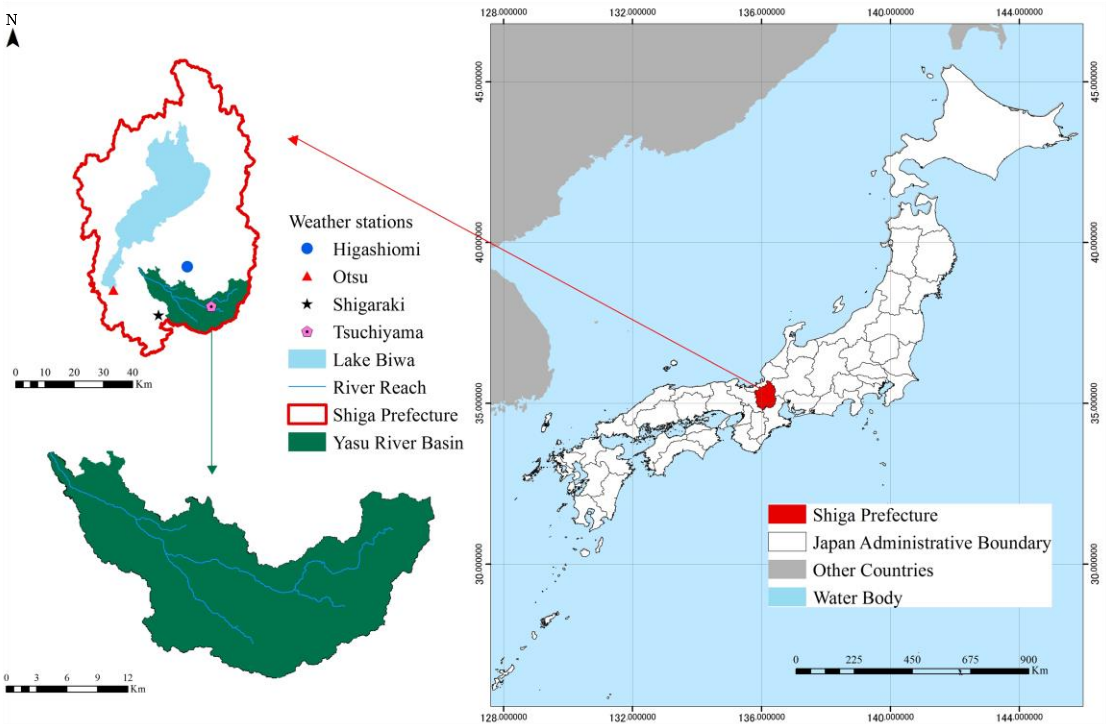

Figure 3.1: Study area

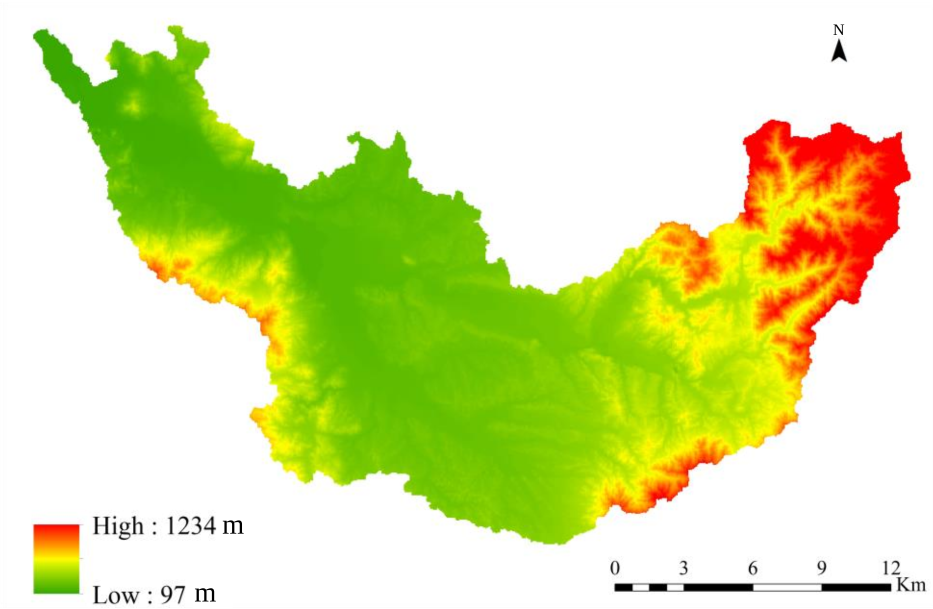

Figure 3.2: Spatial elevation in the study area

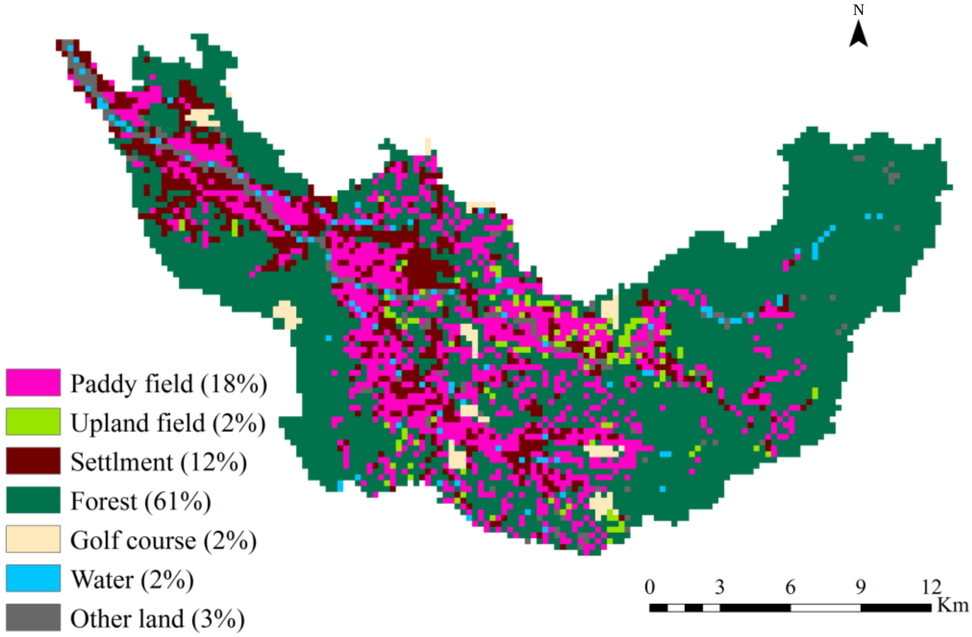

Figure 3.3: Spatial land-use distribution in the study area

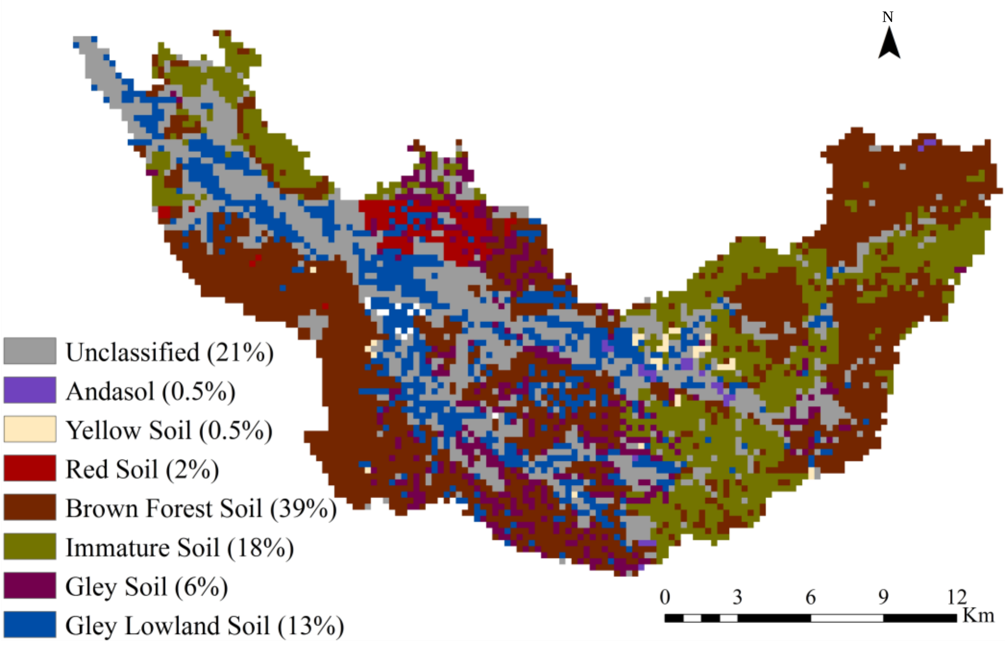

Figure 3.4: Spatial soil distribution in the study area

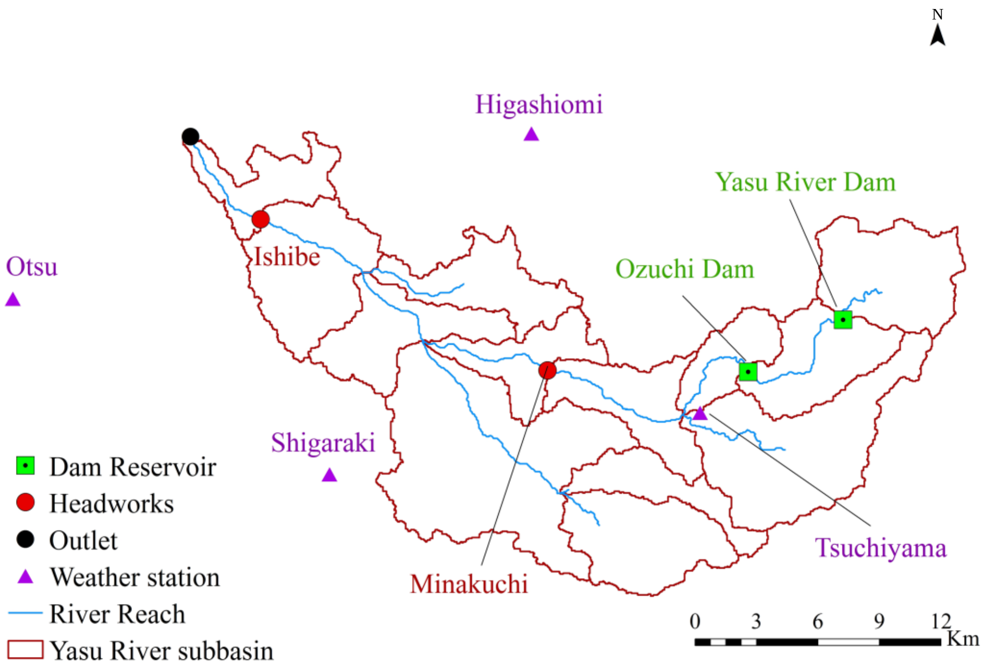

Figure 3.5: Location of climatic stations and hydraulic structures in the study area

overflow data from the Ozuchi and Yasu River Dams. Ozuchi Dam height is 43.5 m with a capacity of 7.3 million m^3 while Yasu river Dam height is 54.4 m with a capacity of 8.5 million m^3. Hydraulic structures regulate the amount of water in the reach. The reservoirs determine the amount of water released from the gate downstream hence the consideration of overflow as input data. Q-GIS (Quantum Geographic Information System) is used as an interface to run SWAT 2012 model. The basin is divided into 13 subbasins and 630 HRUs to represent the diversity within the basin. The length of the reach is distinctive within each subbasin. Water flow is cumulative from one reach to another as it flows from the source to the downstream end.

3.2.2 Irrigation management

Cultivation of rice is the major agricultural activity in the basin. Rice is characterized by high crop water requirement and the field is usually covered with water during irrigation period forming pools. In this study, however, automatic irrigation is used in the model. It triggers water application from the reach to the paddy field when the plant stress level reaches the set criterion. Water is applied upto field capacity and the cycle continues until crop reaches its maturity. Plant water demand is used as the water stress identifier. Water stress threshold that triggers irrigation has a scale of 0 to 1. Water stress threshold of 0.2 is set to trigger irrigation to prevent plant from water deficiency. The amount of maximum water applied each time of irrigation is set as 40 mm with an irrigation efficiency of 0.5. The fraction of surface runoff ratio is set at 0.2. Irrigation source is located at the reach of each subbasin due to headworks abstraction in the field condition. To prevent flow in the reach from being reduced to zero, minimum in-stream flow of 0.01 m^3/s is set. This therefore implies that irrigation water can be diverted from the reach if the flow in the reach is above minimum instream flow. Maximum daily irrigation diversion from the reach is set at 100 mm. The amount of water applied to the HRU cannot exceed the maximum daily irrigation abstraction.

3.2.3 SUFI -2

Sequential Uncertainty Fitting Algorithm (SUFI-2) is used as the optimization program for determining parameter statistical significance, calibration, validation and uncertainty analysis. Its advantage over other techniques is that it requires few model runs to attain good uncertainty ranges hence more data points are captured in prediction uncertainty (Yang *et al*., 2008). In comparing several optimization techniques for uncertainty analysis, different authors have cited advantages of SUFI-2 in terms of model performance, prediction uncertainty and computational efficiency over other techniques (Khoi and Thom, 2015; Emam *et al*., 2018). It has been termed efficient in localizing optimum parameter range in a large scale watershed simulation (Schuol *et al*., 2008; Mehan *et al*., 2017).

SUFI-2 depicts parameter uncertainty as ranges and accounts for all sources of uncertainties expressed as 95% probability distribution in the model output variables. This is calculated at the 2.5% and 97.5% level of cumulative distribution of an output variable derived using Latin hypercube sampling by propagation of parameter uncertainties. This is usually referred to as 95% prediction uncertainty (95PPU). Sampling is carried out, leading to evaluation of objective function corresponding to different parameter sets in the model. The fit between simulated results, 95PPU and observed data is quantified statistically by *P*-factor and *R*-factor. *P*-factor represents the percentage of observed data enveloped by 95PPU of the modeling results while *R*-factor is the thickness of 95PPU envelope (Abbaspour, 2015). Average distance between upper and lower 95PPU is calculated as follows:

$$\bar{d}_X = \frac{1}{N}\sum_{i=1}^{N}(X_U - X_L)_i \tag{3.1}$$

where $\bar{d}_X$ is the average distance between the upper and lower 95PPU, *N* is the number of observation data points, X_U and X_L is the upper 97.5 and lower 2.5 percentiles of cumulative distribution of every simulated point respectively. *P*- and *R*-factors are computed as follows:

$$P = \frac{n^{95ppu}}{N} \tag{3.2}$$

$$R = \frac{\bar{d}_X}{\sigma_X} \tag{3.3}$$

where σ_X is the standard deviation of the measured variable and n^{95ppu} is the number of measured values bracketed by 95PPU. With significance, which is measured by t-test, number of hydrological parameters, sensitivity analysis is carried out to identify the most suitable parameters to be adjusted during calibration period in SUFI-2.

Multi regression analysis is used to determine the significance of parameters. It calculates partial regression coefficients which regress the generated parameters against the objective function. A t-test is used to identify significance of each parameter under the null hypotheses that partial regression is equal to zero. In the t-test, an index t-stat, which is defined as a partial regression coefficient divided by the standard error of the parameter, is used to estimate p-value from the t distribution with n-1 degrees of freedom, where n is the number of parameter sets generated. The larger the absolute value of t-stat the more significant the parameter is, which implies that p-value becomes smaller (Abbaspour, 2015). Eleven objective functions available in SUFI-2 that includes *multiplication of square error, summation of square error,* χ^2*, KEG, NS,* R^2*, PABIAS,* *SSQR*, *RSR*, *MNS* and bR^2 are used to determine parameter sensitivity and their average computed. The performance of the model is evaluated by Nash–Sutcliffe (*NS*) efficiency and coefficient of determination (R^2). The results are evaluated based on a range of $-\infty$ to 1 for *NS* and 0 to 1 for R^2. They are termed satisfactory if *NS* and R^2 are greater than 0.5 (Abbaspour, 2015).

3.3 Results and discussions

3.3.1 Sensitivity analysis

Significant parameters used for model calibration are shown in Table 3.1. They include: Soil conservation service runoff curve number (CN2.mgt), average slope length (SLSUBBSN.hru), base flow recession alpha factor (ALPHA_BF.gw) (days), deep aquifer percolation fraction (RCHRG_DP.gw), channel effective hydraulic conductivity (CH_K2.rte), soil evaporation compensation factor (ESCO.hru), soil saturated hydraulic conductivity (SOL_K.sol) (m/s), and Manning's value of overland flow (OV_N.hru). These values of t-stat and p-value in Table 3.1 are average of those calculated from the eleven objective functions stated in subsection 3.2.2.

3.3.2 Calibration, validation and uncertainty analysis

Calibration period ranges from the year 1992 to 2000. Validation is from the year 2001 to 2009. The number of parameter sets in one iteration is 1000. Uncertainty analysis is conducted together with calibration. CN2.mgt is calibrated for different land-use. Fitted values for soil conservation service runoff curve number are shown in Table 3.2. Land-use in the basin is classified based on SWAT land-use classes therefore other land is represented by general agricultural land.

Soil parameter represented by SOL_K is calibrated for different soil type and layer. Unclassified soil is assigned gleyic properties for soil database in SWAT model before calibration. Two layers are considered, (1) represents the first layer and (2) is the second layer. Fitted values for saturated soil hydraulic conductivity, and other sensitive

Table 3.1: Significant parameters in the study area

Parameter	t-stat	p-value
CH_K2.rte	30.5	0.00100
SLSUBBSN.hru	23.9	6.89 E-30
OV_N.hru	18.2	0.00666
ALPHA_BF.gw	24.6	2.15 E-07
CH_N2.rte	15.4	0.00100
CN2.mgt	12.5	0.00108
ESCO.hru	3.89	0.0335
SOL_K.sol	2.85	0.0310

Table 3.2: Soil conservation service runoff curve number for different land-use parameter

Parameter	Min	Max	Fitted
CN2.mgt_Rice	35	98	95.904
CN2.mgt_Upland fields	35	98	94.288
CN2.mgt_Settlment	35	98	69.948
CN2.mgt_Forest	35	98	86.578
CN2.mgt_Golf course	35	98	91.719
CN2.mgt_Water	35	98	64.492
CN2.mgt_Other land	35	98	72.864

parameters are shown in Tables 3.3, and 3.4, respectively. The results of the model performance based on *NS* and R^2 as well as uncertainty analysis evaluated by *P*- and *R*-factors are shown in Table 3.5. Hydrographs during calibration and validation periods are shown in Figures 3.6 and 3.7.

Table 3.3: Soil saturated hydraulic conductivity

Parameter	Min	Max	Fitted
SOL_K(1).sol_AND	0	2000	530.2
SOL_K(1).sol_BFS	0	2000	267.7
SOL_K(1).sol_GLS	0	2000	1.141
SOL_K(1).sol_GS	0	2000	0.502
SOL_K(1).sol_IMS	0	2000	329.1
SOL_K(1).sol_RDS	0	2000	263.1
SOL_K(1).sol_UNC	0	2000	0.046
SOL_K(1).sol_YES	0	2000	254.1
SOL_K(2).sol_AND	0	2000	398.2
SOL_K(2).sol_BFS	0	2000	50.11
SOL_K(2).sol_GLS	0	2000	0.181
SOL_K(2).sol_GS	0	2000	0.043
SOL_K(2).sol_IMS	0	2000	702.4
SOL_K(2).sol_RDS	0	2000	31.66
SOL_K(2).sol_YES	0	2000	27.94
SOL_K(2).sol_UNC	0	2000	0.035

Table 3.4: Other parameters

Parameter	Min	Max	Fitted
SLSUBBSN.hru	10	150	40.3
ALPHA_BF.gw	0	1	0.882
ESCO.hru	0	1	0.0305
CH_K2.rte	0	150	10.3
CH_N2.rte	0.001	0.3	0.0134
OV_N.hru	0.01	30	3.89

Results based on evaluation performance had values greater 0.5 for both *NS* and R^2, and these values are above required threshold set for evaluation performance described in section 3.2. Observed data enclosed in 95PPU is 82% with uncertainty range of 0.48 during calibration period. Percentage of data enclose in the 95PPU during validation period is 81% with an increase in uncertainty range compared to calibration period. SWAT model application studies conducted within Japan have found almost similar results in model performance for daily streamflow simulation. Studies conducted in the Kashima River watershed in Chiba Prefecture had an average of 0.66 for R^2 and 0.55 for *NS* based on different analysis conducted. The average of *P*- and *R*-factor was 0.93 and 0.79 respectively (Sofiyuddin *et al.*, 2016). Similar range have also been obtained in watersheds outside Japan. Application of SUFI-2 in agricultural watershed in South Dakota (Mehan *et al.*, 2017) had an average of 0.57 R^2 and 0.56 *NS* for the simulation period. *P*- and *R*- factors based on 2000 simulation was 0.94 and 0.65 respectively. It is worth noting that total uncertainty in SUFI-2 is expressed as parameter uncertainty which leads to an equally weighted impact on wet and dry seasons. Challenges in utilizing SUFI-2 includes lacks rigorous probabilistic formulation, parameter uncertainty formulated by uniform distribution in hypercube is propagated but does not consider parameter correlation and inclusion of simulations with poor objective function values (Yang *et al.*, 2008). Based on the results formulated from *P*- and *R*-factors, the parameter prediction uncertainty is relatively large with most of the observed data included in the 95PPU.

The Yasu River basin being highly managed with intensive human activity, it is bound to have numerous conceptual uncertainties. Water management also increases uncertainty within the basin. It is therefore important to capture most of the observed data under the 95PPU with minimum uncertainty range possible.

There is a notable variation in the simulated peak discharge where the model under-predicts peak flow in extreme flooding events. Observed and simulated discharge however corresponds to precipitation pattern in the basin. Figures 3.8 and 3.9 show cumulative discharge and error based on observed and simulated discharge during calibration and validation periods, respectively. The cumulative discharge is high in the observed data as compared to the simulated data for both calibration validation periods.

This depicts overall under estimation of streamflow with notable errors during extreme

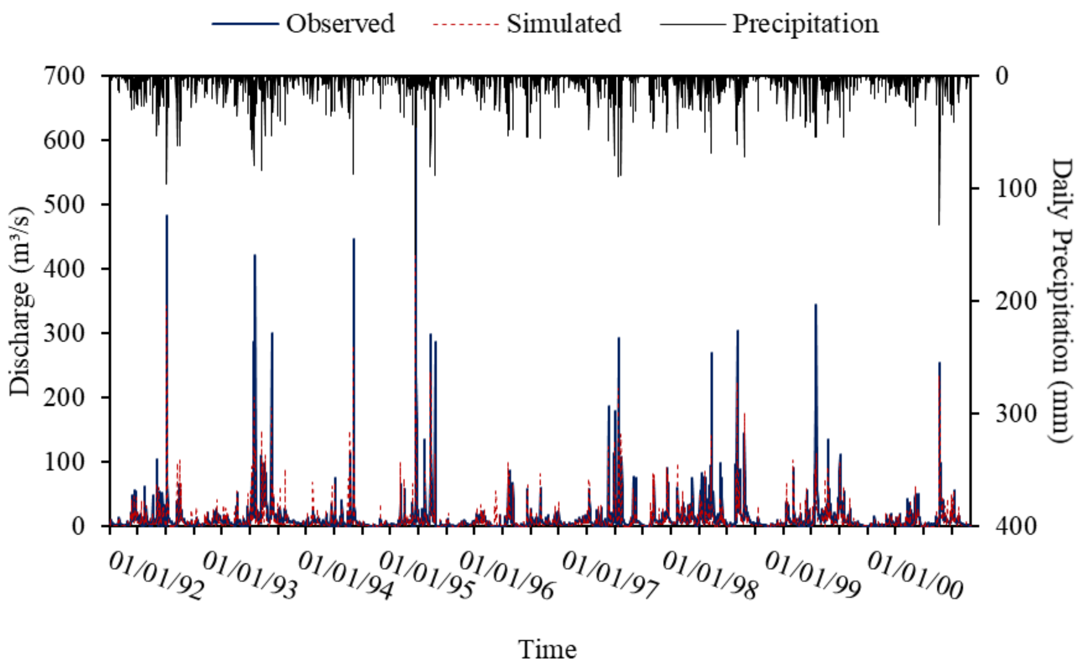

Figure 3.6: Observed and simulated hydrograph during calibration period at the basin outlet

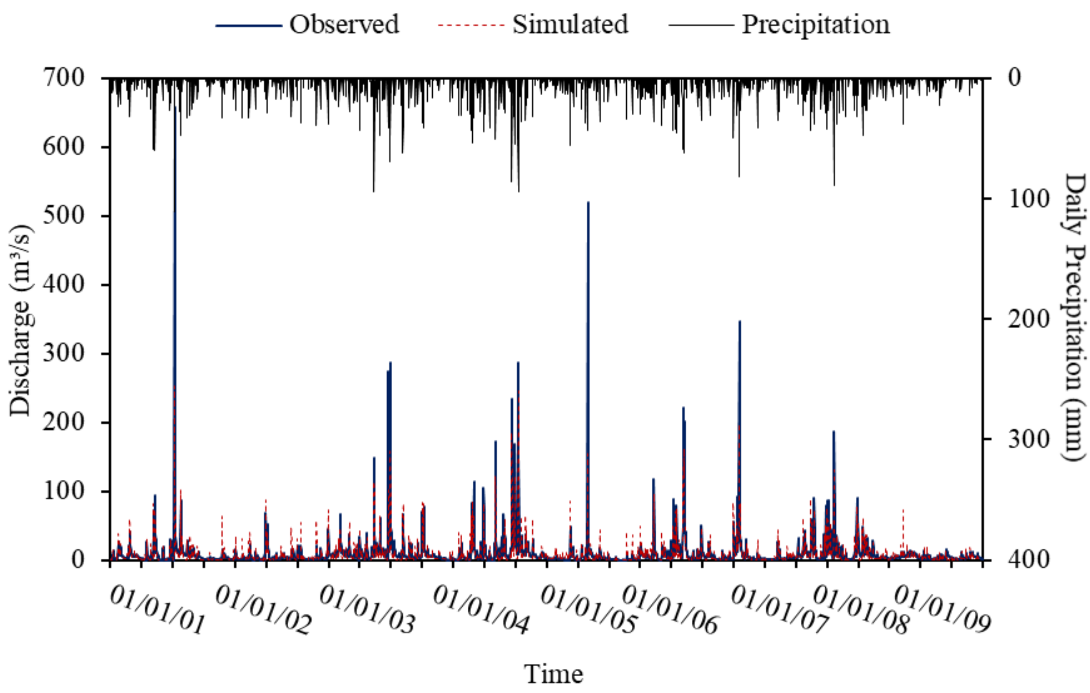

Figure 3.7: Observed and simulated hydrograph during validation period at the basin outlet

Table 3.5: Performance evaluation and uncertainty analysis

	Calibration	Validation
NS	0.72	0.56
R^2	0.70	0.56
P-factor	0.82	0.81
R-factor	0.48	0.53

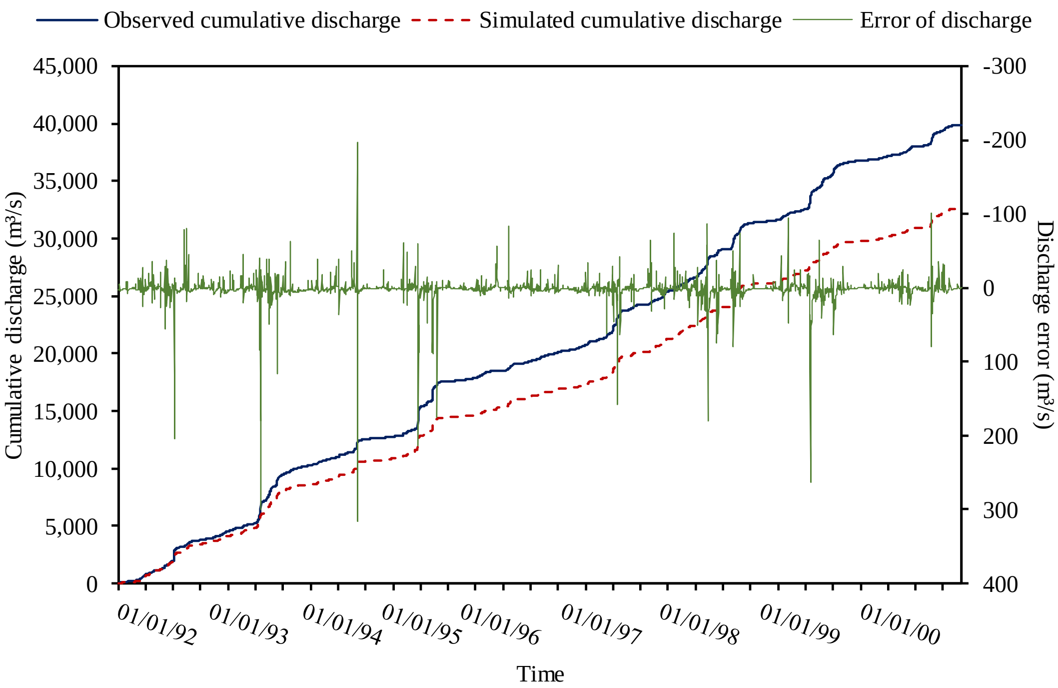

Figure 3.8: Cumulative discharge and error during calibration period

flooding events. Several studies carried out in different catchments have reported under-prediction of peak (Ghoraba, 2015; Wu and Chen, 2015). Possible reasons for inacuracy of peak discharge in the Yasu River basin include limited meteorololgical stations and the extent of distance from one station to another, uncertainty in GIS information for spatial distribution of slope, land-use and soil. There might also be possibilities of limitation of the observed data to accurately record peaks discharge during extreme

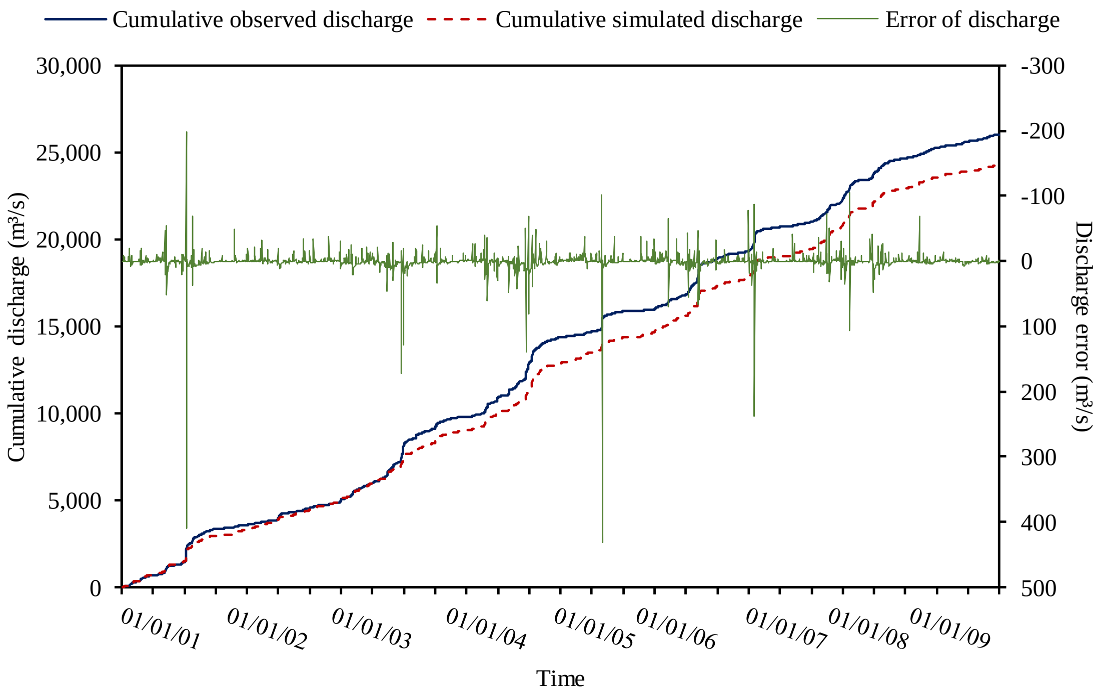

Figure 3.9: Cumulative discharge and error during validation period

flooding period. SWAT model underestimates peak discharge due to the simple curve number method used to model rainfall runoff relationship. Runoff generated by short duration high intensity storm may not be simulated in a large extent (King *et al*., 1999). It should be noted that model calibration is conditional to the type and length of data utilized, the objective function definition, and optimization procedure as well as all other model assumptions (Abbaspour *et al*., 2015). Diversity in different areas presents unique challenges based on the local conditions.

3.4 Conclusion

The study provided an approach for streamflow simulation based on SWAT model in the Yasu River basin. Consequently, sensitivity analysis based on parameter statistical significance, calibration, validation and uncertainty analysis were carried out using SUFI-2 as an optimization program.

Auto irrigation based on crop water requirement was considered during rice cultivation. Daily overflow data from two large reservoirs along the main channel were included in the model. Long term daily streamflow was simulated. Significant parameters were used for model calibration. The model performance had values greater than 0.5 for both *NS* and R^2 during both calibration and validation period. Proportion of the observed data enveloped by 95PPU was 82% and 81% with uncertainty range of 0.48 and 0.53 during calibration and validation periods, respectively. The percentage enveloped by 95PPU is relatively high considering the range of uncertainty. The Yasu River basin being highly managed presents unique challenges coupled with high uncertainties when it comes to a long term daily simulation. Although the model requires significant amount of data and detailed analysis, it is vital for hydrological assessment. The model can be utilized for critical decision making.

CHAPTER 4

Temporal and Spatial Change of Phosphate Phosphorus Concentration and Modeling with Land-use Variation in the Sengari Reservoir Basin, Japan

4.1 Introduction

To improve the quality of life for an increasing global population, the sustainable utilization of natural resources must be realized. Close attention should be paid to the most vulnerable, yet vital, natural resources. Land and water resources play a crucial role in sustaining life. Land cover modification due to changes in land-use intensity has led to widespread pollution that has caused the degradation of water quality (Zhang *et al.*, 2012). One of the detrimental effects that water quality degradation has on the environment is eutrophication (Smith *et al.*, 1998). It has led to the rampant growth of algae and aquatic weeds that have affected the utilization of water for fishing, recreation, agricultural, and domestic use. The economic impact of eutrophication has been felt through the increasing cost of water treatment. Algal growth and the presence of aquatic weeds in water bodies pose a significant threat to aquatic ecosystems as they enhance the depletion of oxygen that occurs during decomposition, causing the suffocation of some aquatic species (Smith *et al*., 1998; Somura *et al*., 2012; Chen et al. 2017).

Authorities in different parts of the world have undertaken various measures to control pollution. Japan has made promising strides in addressing water quality degradation through important policies that target point source pollution. However, it has proven challenging to regulate non-point source pollution due to its complex interaction and the different areas it originates from (Roy, 2007). Sources of non-point source pollution are attributed to different land-uses, particularly agriculture and residential areas associated with urban development. Due to the proliferation of impervious pavement, residential areas have increased surface runoff, which limits the absorption of nutrients in the soil and enables pollutants to easily find their way into water sources in high concentrations. In the agricultural sector, the widespread use of commercial fertilizers has increased the amount of nutrients in water bodies (Carpenter, 2008; Kennen *et al*., 2010; Giri and Qiu, 2016).

The variation of human activities on land over time has increased the complexity of non-point pollution. Reducing the pollution risk can be aided by a greater understanding of the relationship between landscape characteristics and surface water quality (Xiao and Ji, 2007). Land utilization varies depending on the season, especially in agricultural fields. Watershed management can be improved by considering the relationship between landscape characteristics and seasonal variability (Ai *et al.*, 2015). Therefore, analyzing changes in the level of various pollutants during different time periods throughout the year is important for assessing the impact of specific human activities on the watershed. In Japan, the dominant agricultural activity is rice growing that is characterized by irrigation during the cultivation period—from mid-April to September. Non-point source pollutants are therefore not expected to be continuous but rather to vary depending on the activity conducted within the watershed (Carpenter *et al.*, 1998).

Adequate efforts are being made to address non-point source pollution. The development of the geographical information system (GIS) has improved the ability to conduct a spatial analysis of data and has aided watershed management. It has been utilized in various ways in the watershed to analyze geographic data, including climate, topography, and landscape variability (Pratt and Chang, 2012). A combination of GIS, digital land-use data, and multivariate statistics can help researchers approach the complex interactions found in the watershed, ultimately aiding in its effective management (Bahar *et al.*, 2008). Different models have been developed to address non-point source pollution from various land-uses. Many studies have focused on physically based models to address non-point source pollution in different watersheds. While such models can be utilized for decision making, they are time-consuming and require a large amount of data for calibrating the model parameters. Statistical methods are increasingly being used in water resource management. The introduction of regression models has proven to be important in decision-making and has reduced the quantity of data required for modeling (Seilheimer *et al.*, 2013). Ai *et al*. (2015) determined how water contaminants are related to landscape characteristics using partial least square regression. In relating landscape characteristics to non-point sources, Xiao and Ji (2007) used a multiple linear regression model to predict water quality variables. Seilheimer *et al*. (2013) used a mixed-effect regression model to relate landscape and water quality in Lakes Superior and Michigan. Kang *et al*. (2010) used a multiple linear regression model for linking land-use type and stream water quality using data related to fecal indicator bacteria and heavy metals.

This study was conducted in the Sengari Reservoir basin in Japan. The reservoir is affected by eutrophication due to pollutants from different land-uses within the basin. According to Fujiwara (2014), phosphorus is the limiting factor for the reproduction of algae, and about 90% of the total phosphorus (TP) flowing into the reservoir is in the form of phosphate-phosphorus (PO_4-P) at the ordinary level (Hyogo Prefecture, 2016). Various countermeasures, such as underwater aeration and purification by vegetation, have been implemented to reduce phosphorus in the reservoir. However, regardless of such long-term countermeasures, the TP in the reservoir does not satisfy the environmental standard water quality value of 0.01 mg/L (Ministry of Land, Infrastructure, Transport and Tourism, 2016). There are no major industrial load sources in the basin; thus, most of the phosphorus load comes from non-point sources such as agricultural fields, residential areas, and forests. Hence, it is difficult to determine the actual phosphorus load in the basin. The aim of this study is to quantitatively investigate the PO_4-P load emitted from different land-uses by focusing on annual, irrigation, and non-irrigation periods in the Sengari Reservoir basin. Regular water quality measurement along the rivers flowing into the reservoir was conducted to ascertain the temporal and spatial distribution of PO_4-P, and linear multiple regression models were developed to estimate the PO_4-P load from different land-uses within the basin.

4.2 Methodology

4.2.1 Study area

The Sengari Reservoir is located in Hyogo Prefecture of Japan, north of the city of Kobe. It has a water storage capacity of 11.6 million m^3 and supplies 0.119 million m^3 of domestic water a day to Kobe. The total catchment area of the Sengari Reservoir basin is about 94.5 km^2 and the basin is characterized by a steep, undulating topography. Two major rivers, the Hatsuka River and Hazu River, flow into the reservoir. In this study, the two river basins are divided into two and four subbasins, respectively, as shown in Figure 4.1. The Hatsuka River basin is divided into the Hatsuka and Sueyoshi subbasins, and the Hazu River basin is divided into the Hazu, Sasori, Nagatani, and Oharano subbasins. The dominant land-uses in the basin include forests, paddy fields, and residential areas. Land-use ratios in each subbasin are shown in Table 4.1. Wastewater generated from houses in the basin is treated by rural sewage plants or septic tanks. The subbasins with rural sewage plants include Hatsuka, Sueyoshi, and Hazu, while septic tanks were installed in each house to treat wastewater in Sasori, Nagatani, and Oharano.

4.2.2 Data collection and analysis

To evaluate PO_4-P concentrations in the basin, water samples were collected along the Hatsuka and Hazu rivers in six subbasins. A total of 92 sampling points were analyzed in the entire basin—the locations of these points are shown in Figure 4.1 and their index is given from upstream to downstream in each subbasin. In Figure 4.1, only indices of the most upstream and downstream ones are shown. To examine the variation of PO_4-P over time in different seasons, samples were collected during the irrigation period and non-irrigation period, as shown in Table 4.2. The irrigation period is represented by the shaded area in the months of May, June, and July, while the unshaded area represents the months of the non-irrigation period. Water samples were collected regularly along the rivers in the six subbasins—on consecutive months in the irrigation period and once every two months in the non-irrigation period.

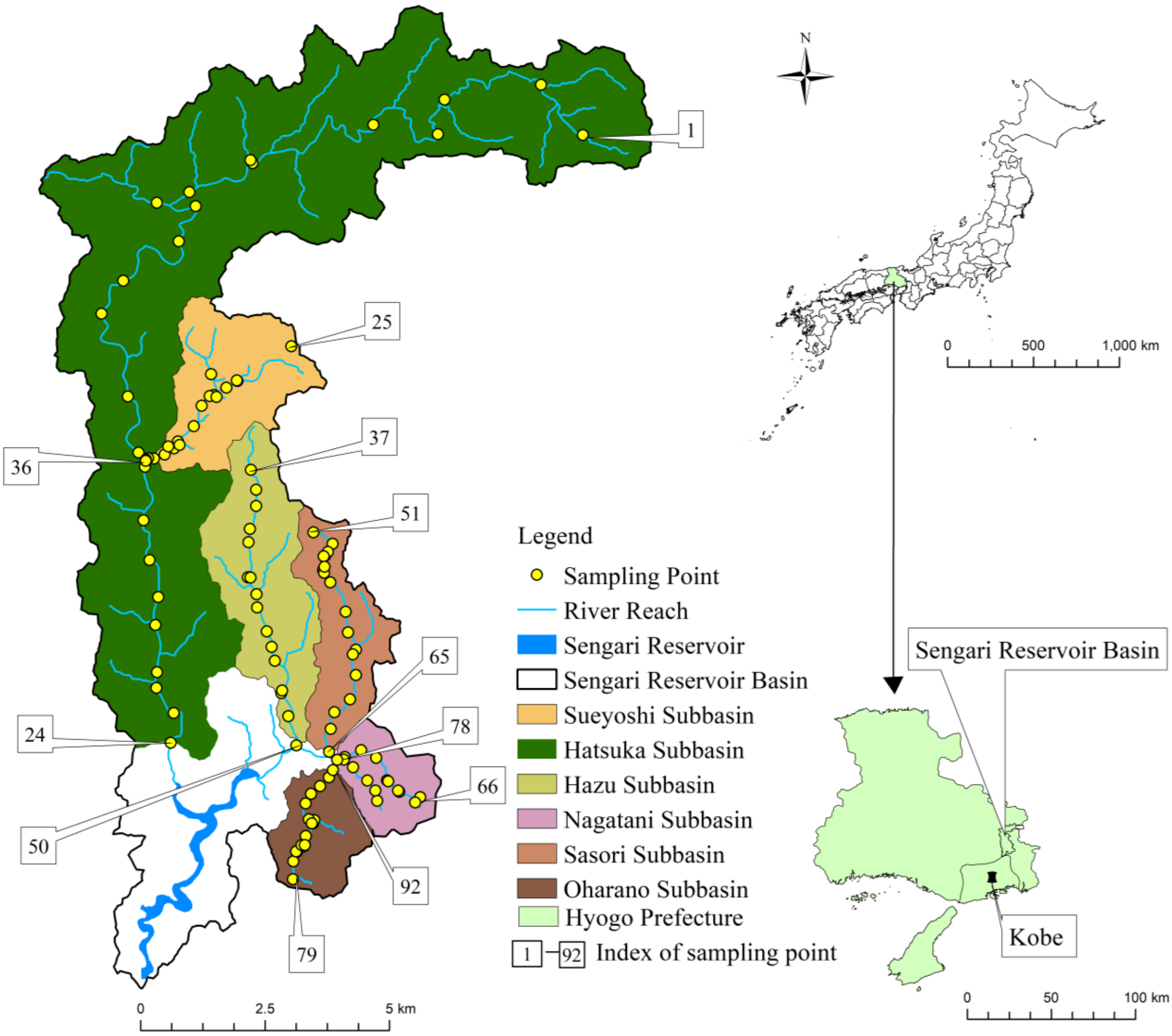

Figure 4.1: Study area

Table 4.1: Percentage of land-use ratio in each subbasin

Subbasin	Sampling Point	Area (km²)	Forest (%)	Paddy Field (%)	Resident Area (%)	Golf Course (%)	Others (%)
Hatsuka	1-24	60.67	87.52	9.3	1.51	0.77	0.88
Sueyoshi	25-36	6.74	86.46	8.76	0.41	4.24	0
Hazu	37-50	8.41	91.66	8.23	0.11	0	0
Sasori	51-65	5.26	83.93	13.71	1.52	0.51	0.34
Nagatani	66-78	3.13	74.77	13.23	2.15	9.85	0
Oharano	79-92	3.6	70.03	21.16	7.05	0	1.76

Table 4.2: Data collection dates

Time	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Year	2016				2017					
1st day	6/3	7/19	10/11	12/12	2/20	4/27	5/25	6/23	7/27	11/13
2nd day	6/10	7/22	10/13	12/13	2/21	4/28	5/26	6/24	7/28	11/24

Shaded dates are in the irrigation period.

Rainy days and days immediately after rainfall were avoided to obtain samples at an ordinary water level. The collected water samples were served without any digestion to measure the concentration of PO_4-P, and the concentration was measured with a Digital Pack Test (DPM-PO4-PD, Kyoritsu Chemical-Check Lab. Co.) and Photometer (YSI 9500, xylem). Their measuring ranges are 0.03–1.00 mg/L and 0.00–1.30 mg/L, respectively, with a 0.01 mg/L resolution. YSI 9500 was introduced because the PO_4-P concentration in many samples was below the detectable limit of the DPM-PO4-PD. The average concentration was computed at each sampling point and analyzed during annual, irrigation, and non-irrigation periods.

The spatial data including the Digital Elevation Model (DEM) and land-use mesh data were obtained from the Geospatial Information Authority of Japan. ArcGIS 10.5 was used for spatial data analysis and DEM was used to delineate the basin into 92 subbasins representing each sampling point. The land-use ratio was derived from a given sampling point of the subbasin by dividing the land-use area by the area of the subbasin.

4.2.3 Linear multiple regression model

The linear multiple regression model is developed to estimate PO_4-P concentrations and is based on the land-use correlation. At first, the following steady model was assumed to estimate the PO_4-P load at a specific sampling point:

$$cQ = R\sum_i \alpha_i c_i A_i \tag{4.1}$$

where c is the concentration of PO_4-P at a particular sampling point along the river, Q ($=\alpha RA$) is the discharge, R is the amount of rainfall, α is the runoff ratio to the rainfall, A is the catchment area of the sampling point, and the subscript i ($\in$ {forest, paddy field,…}) indicates a member of the land-use set. Variables without the subscript i represent the catchment area of a given sampling point. This model considers all PO_4-P loads that can reach the sampling point through the river from each land-use type. Being divided by Q and adding an error term u, this model can be regarded as a linear multiple regression model to estimate the PO_4-P concentration at a sampling point.

$$c = \sum_i \beta_i X_i + u \tag{4.2}$$

where β_i ($= \alpha_i c_i / \alpha$) are the regression coefficients, and X_i ($= A_i / A$) are the explanatory variables. In addition, other explanatory variables can be considered in the model. Here, the objective area ratio to the subbasin and the dummy variable that represents the type of wastewater treatment are considered.

$$X_{\text{arearatio}} = A / A_{\text{subbasin}} \tag{4.3}$$

$$X_{\text{dummy}} = \begin{cases} 0 & \text{rural sewage} \\ 1 & \text{septic tank} \end{cases} \quad \text{or} \quad X_{\text{dummy}} = \begin{cases} 1 & \text{rural sewage} \\ 0 & \text{septic tank} \end{cases} \tag{4.4}$$

where A_{subbasin} is the area of the subbasin to which a given sampling point belongs. This explanatory variable "Area Ratio" represents the relative location of an objective sampling point in the subbasin. The value becomes small when the sampling point is in the upstream, and it becomes large when in the downstream within the range from 0 to 1. This is considered to capture the purification effect of the PO_4-P concentration as it moves from upstream to downstream and the dilution by groundwater discharge that contains a low PO_4-P concentration. Dummy variables consider the effect of septic tanks and sewage treatment plants in the model. This study tested the twelve model scenarios listed in Table 4.3. In the Model 1 and 2 groups, three and four major land-use types are used as explanatory variables, respectively. The land-uses considered in the analysis include forest, paddy fields, residential areas, and golf courses. Other land-uses are not evaluated due to their insignificant land-use ratio within the basin. The performance of the models

Table 4.3: Data collection dates

Model	Explanatory Variables
1-1	Forest, Paddy Field, Residential Area
1-2	Model 1-1 + area ratio
1-3	Model 1-1 + septic tank dummy variable
1-4	Model 1-1 + sewage treatment plant dummy variable
1-5	Model 1-1 + area ratio, septic tank dummy variable
1-6	Model 1-1 + area ratio, sewage treatment plant dummy variable
2-1	Forest, Paddy Field, Residential Area, Golf Course
2-2	Model 2-1 + area ratio
2-3	Model 2-1 + septic tank dummy variable
2-4	Model 2-1 + sewage treatment plant dummy variable
2-5	Model 2-1 + area ratio, septic tank dummy variable
2-6	Model 2-1 + area ratio, sewage treatment plant dummy variable

is evaluated by the Akaike information criteria (AIC). The best estimation is made based on the lowest value generated by AIC.

4.3 Results and discussions

4.3.1 Annual average

Regression coefficients

Table 4.4 shows the regression coefficients obtained using the annual average data of PO_4-P for Models 1 and 2 of the different explanatory variables scenarios. In Model 1, “paddy field” has the highest coefficient, followed by “residential area” and “forest”, respectively. In Model 2, “golf course” yielded a negative coefficient. This indicates that golf courses do not discharge PO_4-P and may act as a sink for the nutrient. The coefficients obtained suggest that paddy fields and residential areas have a higher production of PO_4-P, while forests have the lowest production. This ranking of instream TP is supported by Tong and Chen (2002) who obtained similar results.

Agricultural land has been identified as the major contributor to surface water pollution in several basins (Hoorman *et al.*, 2008; Zhang *et al.*, 2012). Residential areas have relatively high coefficients that are close to those of agricultural areas. Urban land-use is considered to have a massive influence on water contaminant variables. Rivers flowing through urban areas have been reported to have high nutrient loads (Ai *et al.*, 2015; Meyer *et al.*, 2005). Forest areas yield the lowest coefficients in the Sengari Reservoir basin. In fact, some studies, such as Mochizuki *et al.* (2013), have exhibited negative coefficients in forest areas. Ogawa (2005) suggested that forests can either be a polluting source or have a purifying effect, depending on the basin. The positive low coefficient of forests in the basin makes them a pollutant source, but with low concentrations of TP. When the catchment area effect is considered, the area ratio coefficient yields negative values, which implies a reduction of PO_4-P due to purification during the upstream to downstream flow and/or dilution through the resurgence of groundwater. When the effect of septic tanks, represented by a dummy variable, is considered (Models 1-3, 1-5, 2-3, and 2-5), positive coefficients are obtained. This indicates the additional production effect of PO_4-P in the basin due to septic tanks compared with rural sewage treatment subbasins. The model yielded a negative coefficient when considering sewage treatment plant (Models 1-4, 1-6, 2-4, and 2-6), implying a reduction effect compared with septic tank subbasins. This is consistent with the field-observed concentrations shown in Figure 4.2, where subbasins with septic tanks have a higher concentration of PO_4-P compared to sewage treatment plant subbasins.

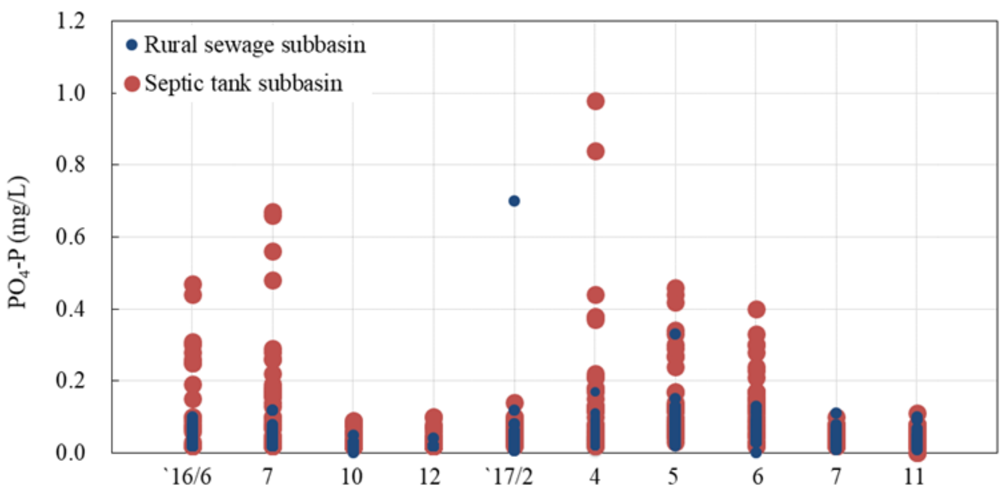

Figure 4.2: PO_4-P concentrations in rural sewage subbasins (1 to 50) and septic tank subbasins (51 to 92) at different sampling dates

Table 4.4: Annual model performance and coefficients

Model	AIC	Forest	Paddy Field	Residential Area	Golf Course	Area Ratio	Dummy Variable
1-1	-296.9	0.032	0.424	0.204	-	-	-
1-2	-307.4	0.054	0.474	0.381	-	-0.049	-
1-3	-311.8	0.027	0.238	0.196	-	-	0.044
1-4	-317.4	0.083	0.251	0.193	-	-	-0.051
1-5	-316.8	0.043	0.307	0.265	-	-0.031	0.036
1-6	-318.4	0.085	0.328	0.221	-	-0.027	-0.043
2-1	-295.2	0.034	0.417	0.193	-0.006	-	-
2-2	-305.8	0.055	0.473	0.377	-0.014	-0.049	-
2-3	-318.6	0.036	0.160	0.093	-0.179	-	0.058
2-4	-318.7	0.095	0.219	0.150	-0.120	-	-0.058
2-5	-319.4	0.046	0.238	0.167	-0.149	-0.024	0.048
2-6	-319.3	0.094	0.296	0.171	-0.103	-0.024	-0.049

Observed and estimated values

The spatial distribution of observed PO_4-P concentration is as shown in Figure 4.3. The figure shows varying concentration levels at various points in the basin. The concentration ranges from 0.02 to 0.05 mg/L in Hatsuka subbasin, 0.02 to 0.09 mg/L in Sueyoshi subbasin, 0.03 to 0.06 mg/L in Hazu subbasin, 0.02 to 0.25 mg/L in Sasori subbasin, 0.03 to 0.08 mg/L in Nagatani subbasin and 0.04 to 0.24 mg/L in Oharano subbasin. Spatial variability of the concentration is influenced by land use activities in the basin. The comparison between observed and estimated values for each sampling point is shown in Figures 4.4 and 4.5. The vertical axis represents PO_4-P concentration and the horizontal axis shows the index of the sampling points. The figure shows that there was relatively good estimation in the rural sewage subbasins (from 1 to 50) compared to that in the septic tank subbasins (from 51 to 92). There are relatively large deviations at around points 58 and 78, which implies the existence of some irregular PO_4-P sources (further investigation revealed that there is a livestock waste treatment site or a cowshed in the area). The estimated values get better as the number of explanatory variables increases. Scenarios 5 and 6, which consider land-use, catchment area, and dummy variables, had the lowest AIC values however all models can be utilized as the difference in AIC value is small. Additional explanatory represents the existing condition of the basin activities.

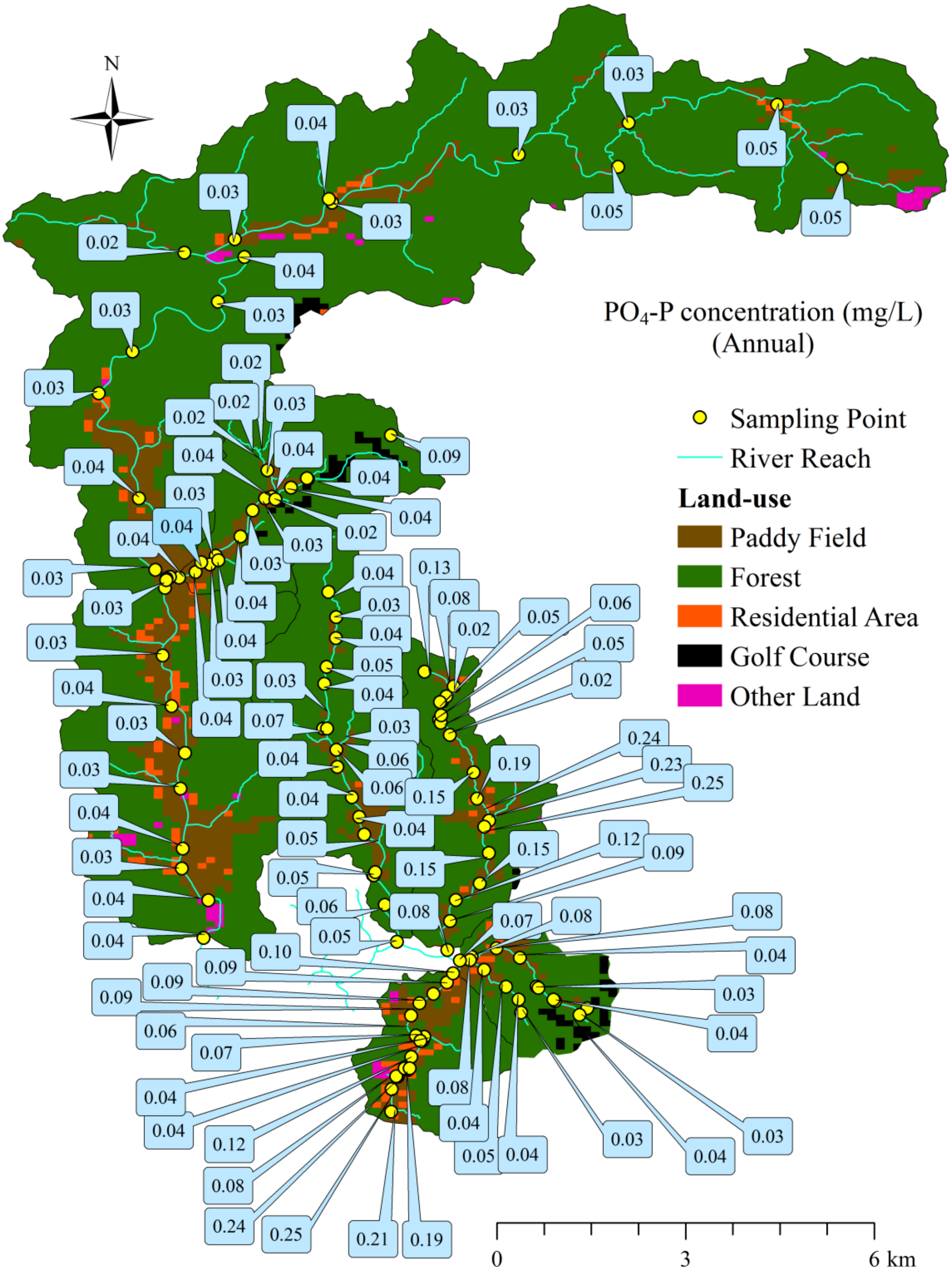

Figure 4.3: Spatial distribution of annual observed concentration

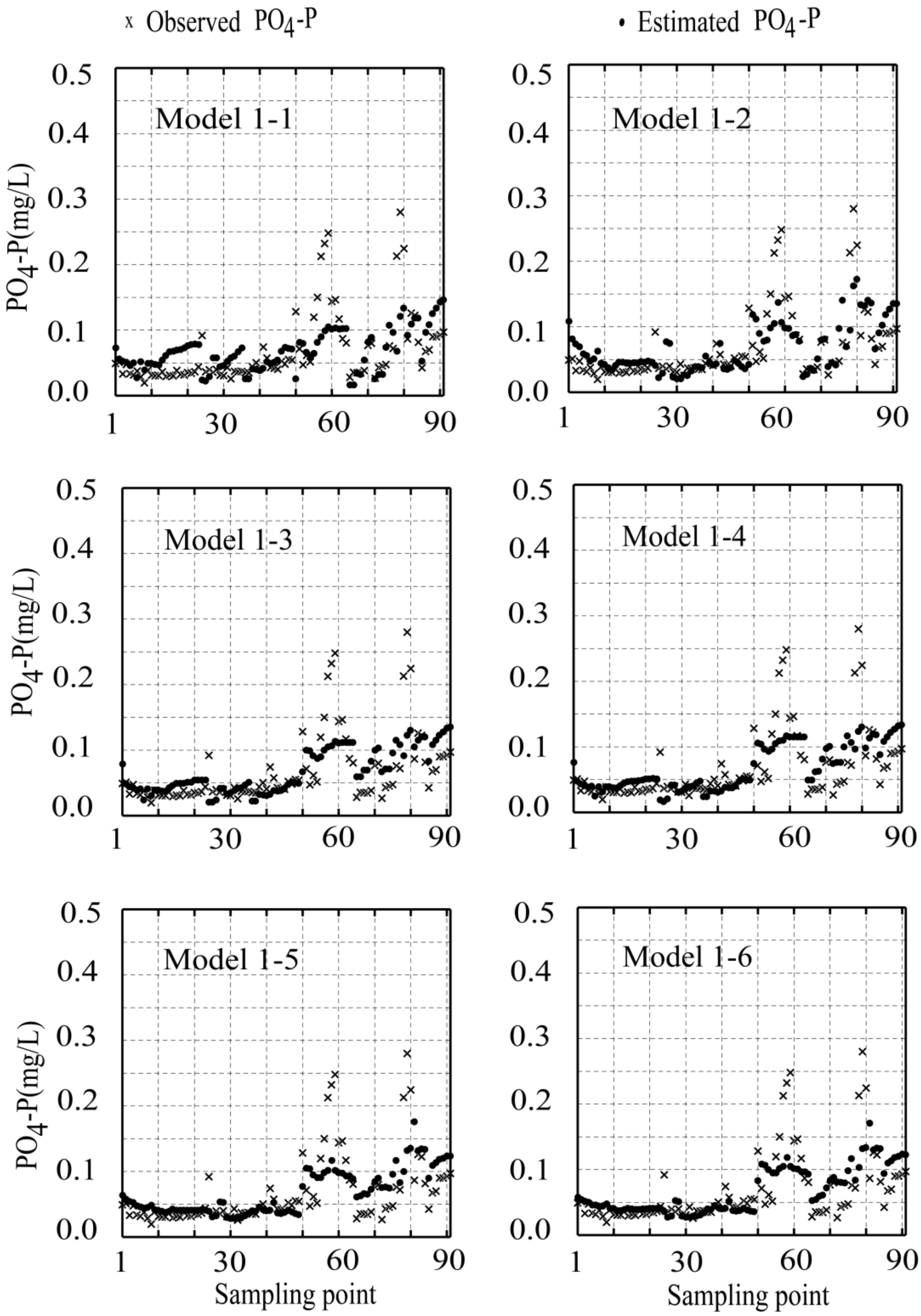

Figure 4.4: Annual observed and estimated PO_4-P concentrations for Model 1

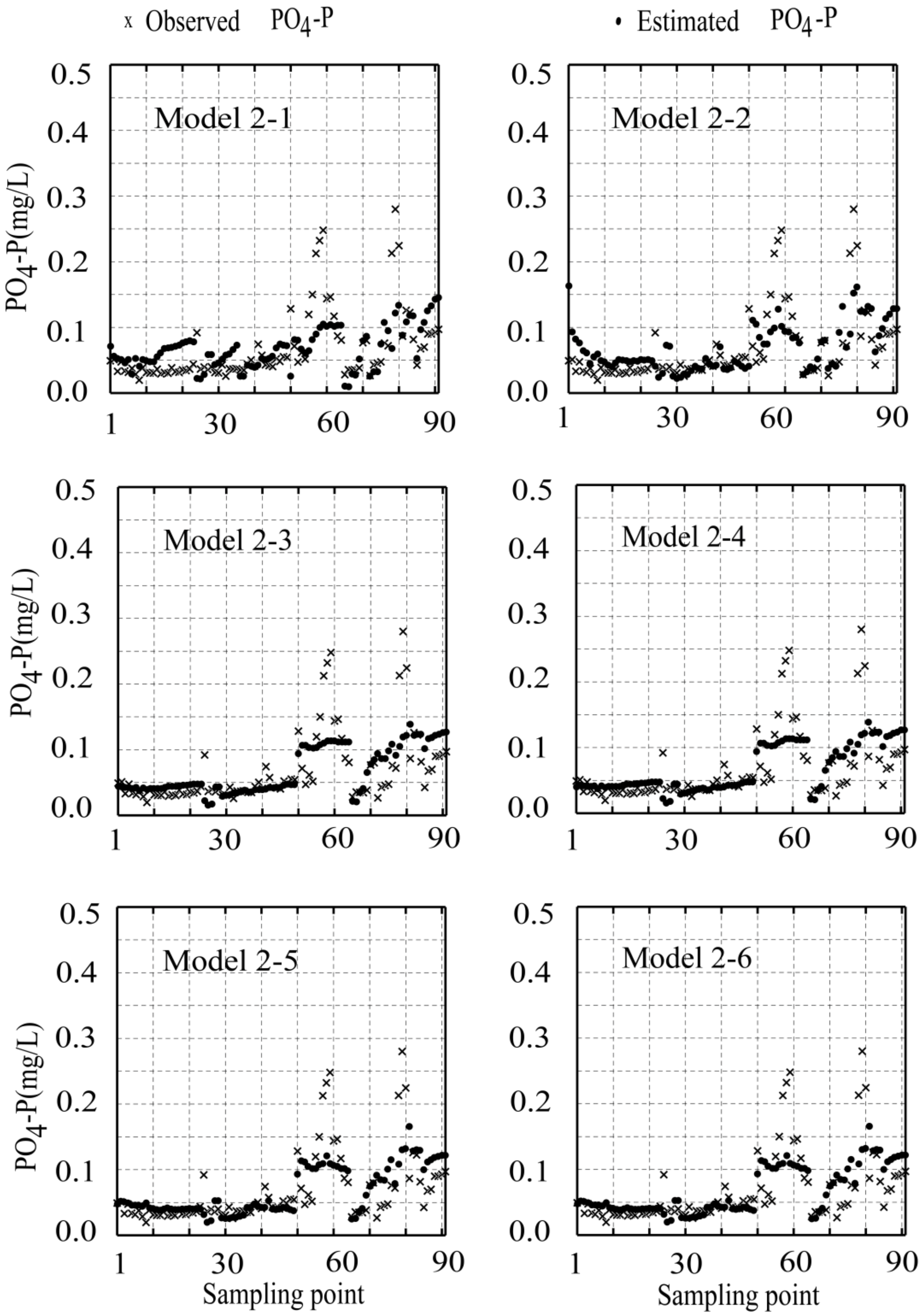

Figure 4.5: Annual observed and estimated PO_4-P concentrations for Model 2

4.3.2 Irrigation and non-irrigation period analysis

Regression coefficients

The following section considers the analysis of the irrigation and non-irrigation periods. Tables 4.5 and 4.6 show the regression coefficients during the irrigation period and non-irrigation period, respectively. Both Models 1 and 2 depict higher regression coefficients during the irrigation period compared to the non-irrigation period. The difference in coefficients is attributed to farming operations, such as paddling and fertilizer application in the paddy fields conducted during the irrigation period. According to Roy (2007), agricultural chemicals and fertilizers are mixed with the water used to irrigate the field in most instances. Water is stored in paddy fields, except for mid-summer drainage, and this condition makes it easier for water to run off from the fields when it rains during the irrigation period. Furthermore, the water inundation typical of paddy fields makes water and soil aerobic and creates a reduction condition, which leads to the elution of phosphorus from soil particles.

The general trend in land-use coefficients during the irrigation and non-irrigation periods depicts paddy fields and residential areas as the major pollutants. Residential areas have high runoff coefficient accelerating pollutants movement. There is a notable decrease in the paddy field coefficient during the non-irrigation that can be attributed to decreased farming activities in that time. However, the paddy field coefficient is still high compared to other land-uses in the non-irrigation period. This may be attributed to the high concentration of nutrients that paddy fields absorb into their soil due to the continuous cultivation of rice every season. A decline in the residential area coefficient during the non-irrigation period may be caused by a decline in the daily average water supply from October to May compared with the irrigation period (Ministry of Land, Infrastructure, Transport and Tourism, 2016). Less wastewater emission leads to a decline in the residential area coefficients, because the coefficients include runoff ratio as shown in Equations (4.1) and (4.2).

Table 4.5: Model performance and coefficients during the irrigation period

Model	AIC	Forest	Paddy Field	Residential Area	Golf Course	Area Ratio	Dummy Variable
1-1	-194.6	0.042	0.630	0.592	-	-	-
1-2	-203.3	0.072	0.791	0.620	-	-0.083	-
1-3	-209.8	0.033	0.368	0.274	-	-	0.076
1-4	-212.5	0.126	0.392	0.296	-	-	-0.091
1-5	-210.3	0.051	0.456	0.371	-	-0.044	0.068
1-6	-212.8	0.131	0.483	0.373	-	-0.038	-0.080
2-1	-192.6	0.043	0.629	0.590	-0.015	-	-
2-2	-201.7	0.076	0.786	0.612	-0.035	-0.084	-
2-3	-214.1	0.044	0.228	0.133	-0.322	-	0.104
2-4	-214.1	0.148	0.332	0.237	-0.218	-	-0.104
2-5	-213.7	0.055	0.317	0.223	-0.286	-0.032	0.093
2-6	-213.7	0.149	0.410	0.316	-0.193	-0.032	-0.093

Table 4.6: Model performance and coefficient during the non-irrigation period

Model	AIC	Forest	Paddy Field	Residential Area	Golf Course	Area Ratio	Dummy Variable
1-1	-516.6	0.025	0.168	0.159	-	-	-
1-2	-530.9	0.031	0.217	0.168	-	-0.018	-
1-3	-518.4	0.023	0.162	0.038	-	-	0.009
1-4	-518.4	0.032	0.171	0.047	-	-	-0.009
1-5	-532.0	0.029	0.207	0.100	-	-0.016	0.005
1-6	-532.1	0.035	0.208	0.104	-	-0.015	-0.006
2-1	-515.4	0.024	0.172	0.158	0.019	-	-
2-2	-530.0	0.031	0.221	0.170	0.020	-0.019	-
2-3	-519.7	0.025	0.134	0.033	-0.021	-	0.012
2-4	-519.7	0.037	0.146	0.045	-0.008	-	-0.012
2-5	-528.1	0.029	0.203	0.116	0.005	-0.016	0.005
2-6	-528.4	0.035	0.203	0.123	0.008	-0.015	-0.006

Observed and estimated values

Figures 4.6 and 4.7 show the spatial distribution of observed concentrations during irrigation and non-irrigation period respectively. There is a notable spatial difference in PO_4-P concentration during irrigation and non-irrigation period at different sampling points. Irrigation period has higher PO_4-P concentration compared to non-irrigation period. During irrigation period, concentration ranges from 0.02 to 0.06 mg/L in Hatsuka subbasin, 0.02 to 0.09 mg/L in Sueyoshi subbasin, 0.03 to 0.12 mg/L in Hazu subbasin, 0.08 to 0.43 mg/L in Sasori subbasin, 0.03 to 0.12 mg/L in Nagatani subbasin and 0.03 to 0.57 mg/L in Oharano subbasin. During non-irrigation period, concentration ranges from 0.02 to 0.06 mg/L in Hatsuka subbasin, 0.02 to 0.09 mg/L in Sueyoshi subbasin, 0.02 to 0.04 mg/L in Hazu subbasin, 0.02 to 0.12 mg/L in Sasori subbasin, 0.02 to 0.4 mg/L in Nagatani subbasin and 0.03 to 0.07 mg/L in Oharano subbasin.

Figures 4.8 and 4.9 show a comparison between the observed and estimated values in each sampling-point during the irrigation period while Figures 4.10 and 4.11 represent non-irrigation period. The estimated values show a promising trend in the non-irrigation period that is enhanced by a decline in land-use activities during that time. There is a significant difference in PO_4-P concentration between irrigation and non-irrigation periods in septic tank subbasins (point 51-92). About the half of the rising in the observed concentration (up to about 0.2 mg/L) can be explained by this linear multiple regression model. Namely, the increase of the coefficients in the paddy fields and residential areas and the relatively large areas occupied by these two land-use types in the septic tank subbasins (Table 4.1) are the reason. Another half of rising in the concentration (over 0.2 mg/L) is considered to be related to the factor that is not included in this model such as the livestock waste treatment site and cowshed. The cause of the increase of those effects and the coefficients especially in the residential areas during the irrigation period are considered to be related to temperature and/or other chemical properties, but those are beyond the scope of this study.

An evaluation of the model also suggests that the models perform better in the non-irrigation period due to low AIC values compared to the irrigation period. It is evident that land-use activities increase the complexity of interaction between non-point source

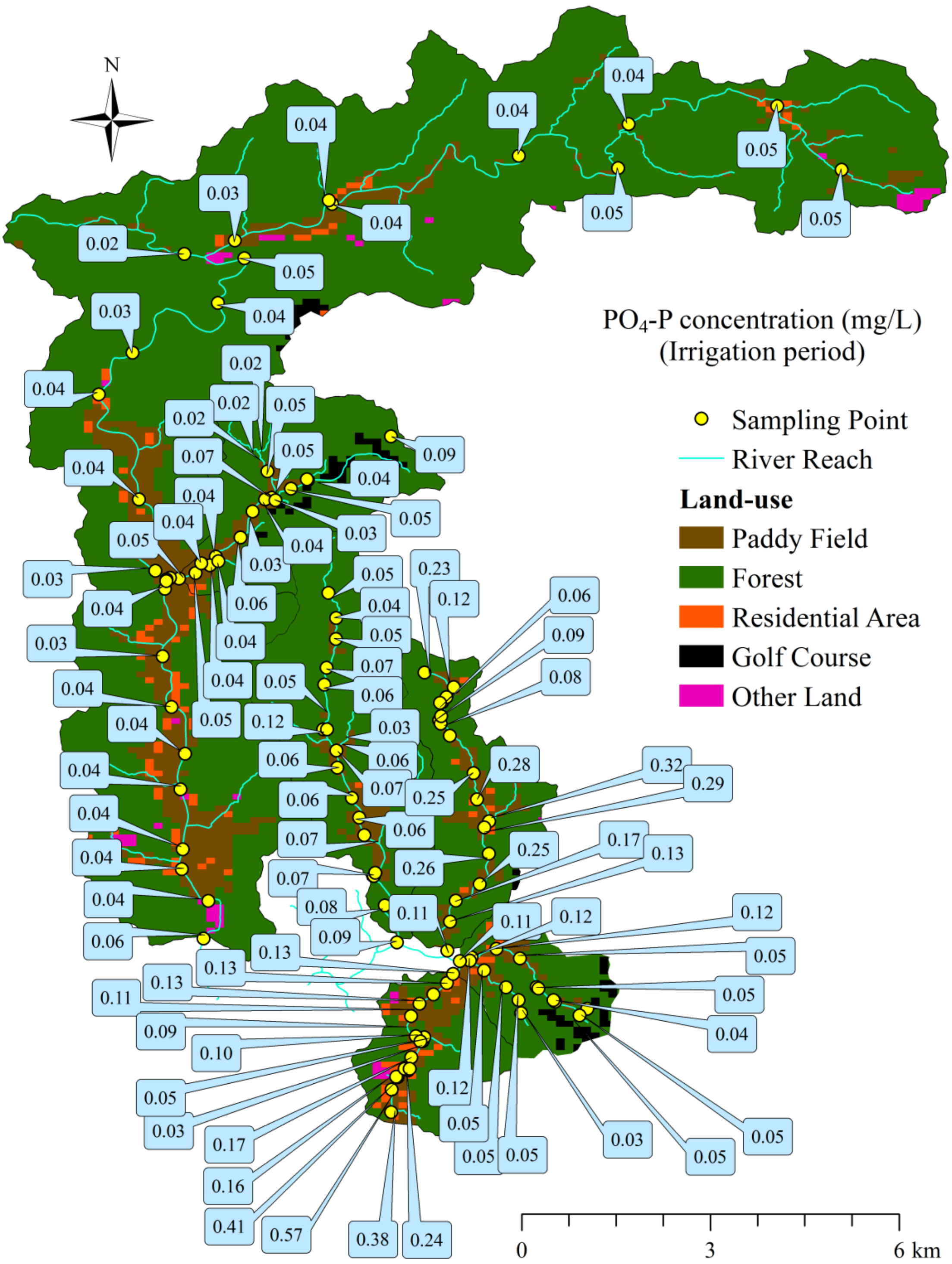

Figure 4.6: Spatial distribution of observed concentration during the irrigation period

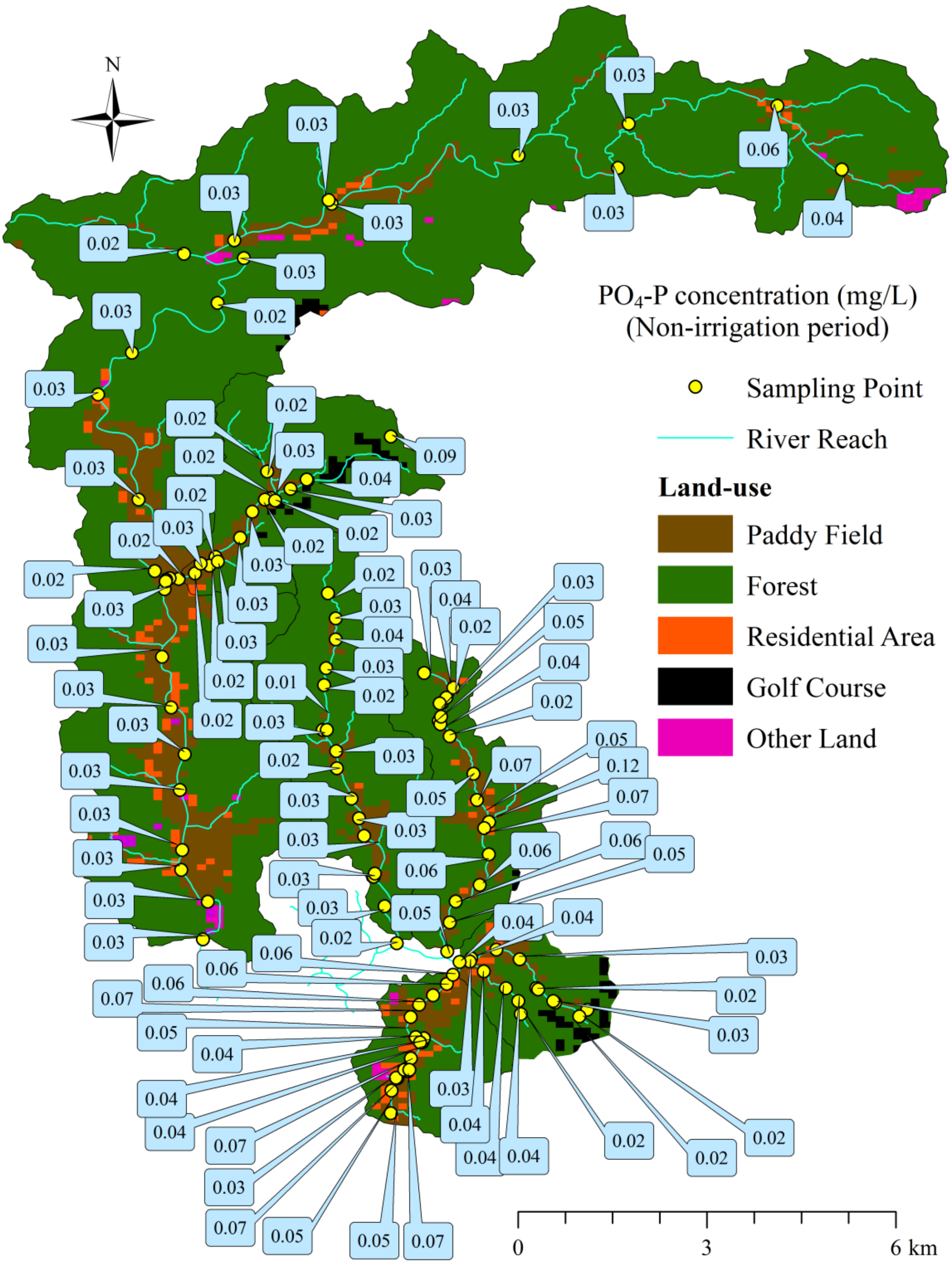

Figure 4.7: Spatial distribution of observed concentration during the non-irrigation period

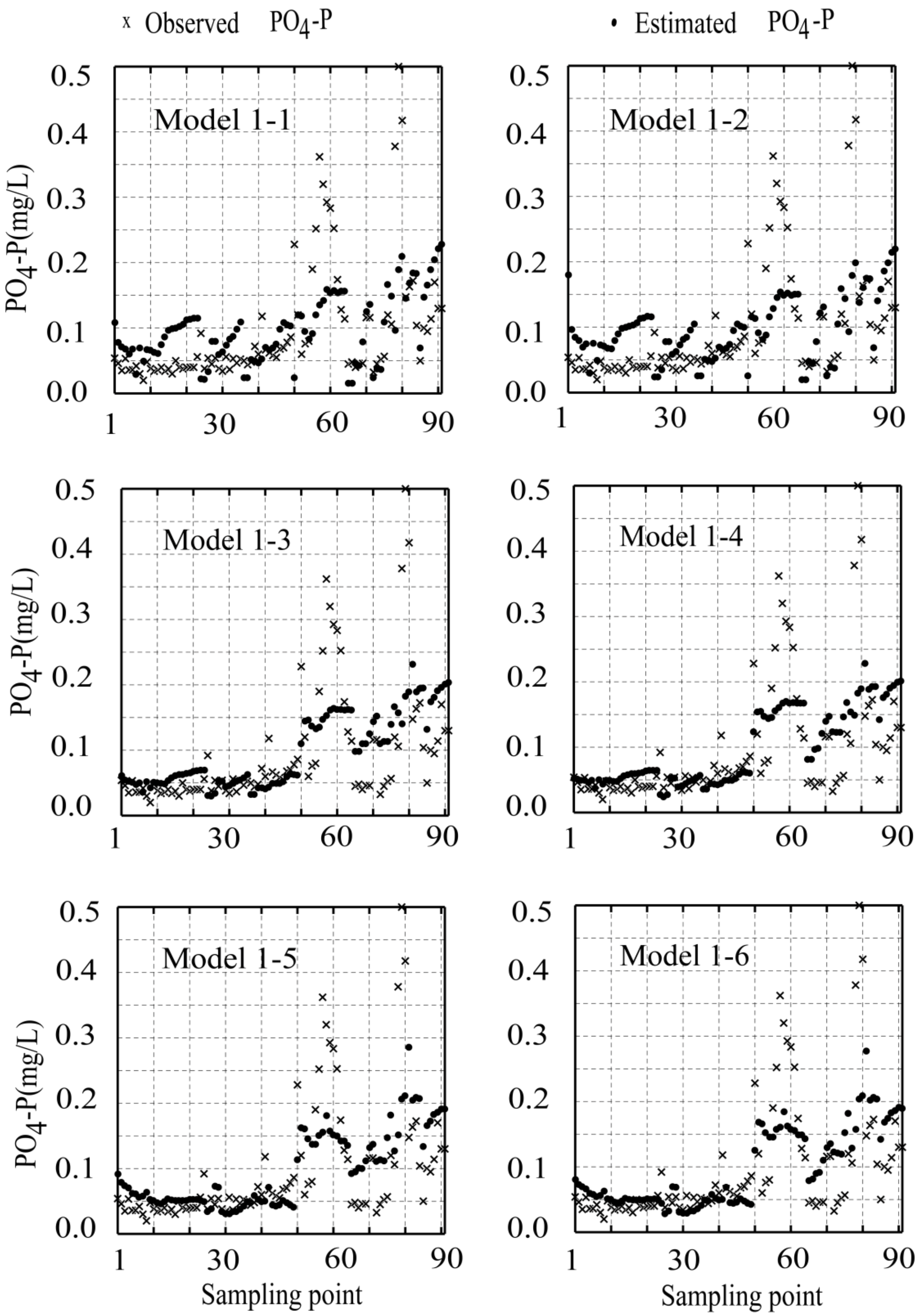

Figure 4.8: Observed and estimated PO_4-P concentration during the irrigation period for Model 1

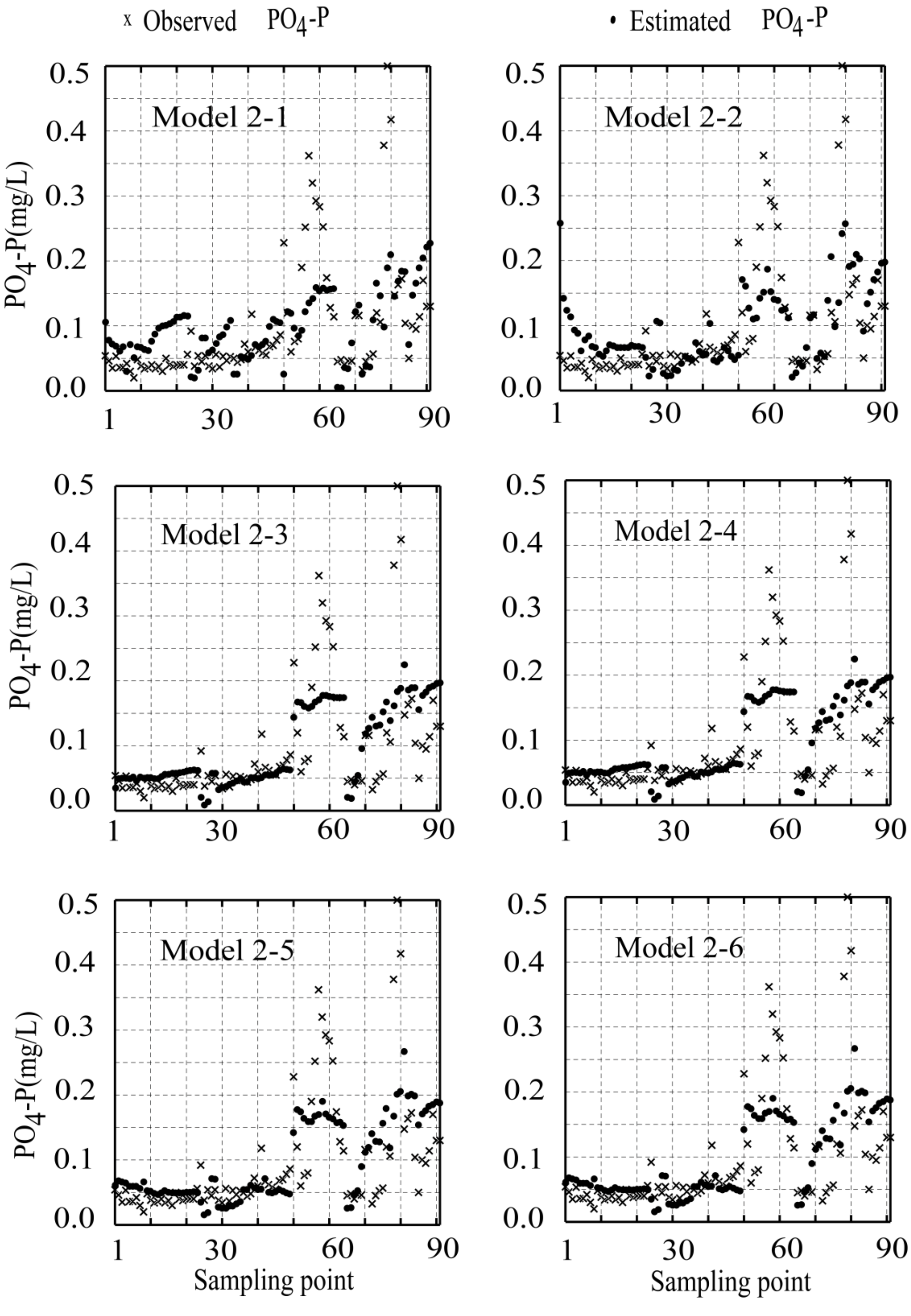

Figure 4.9: Observed and estimated PO_4-P concentration during the irrigation period for Model 2

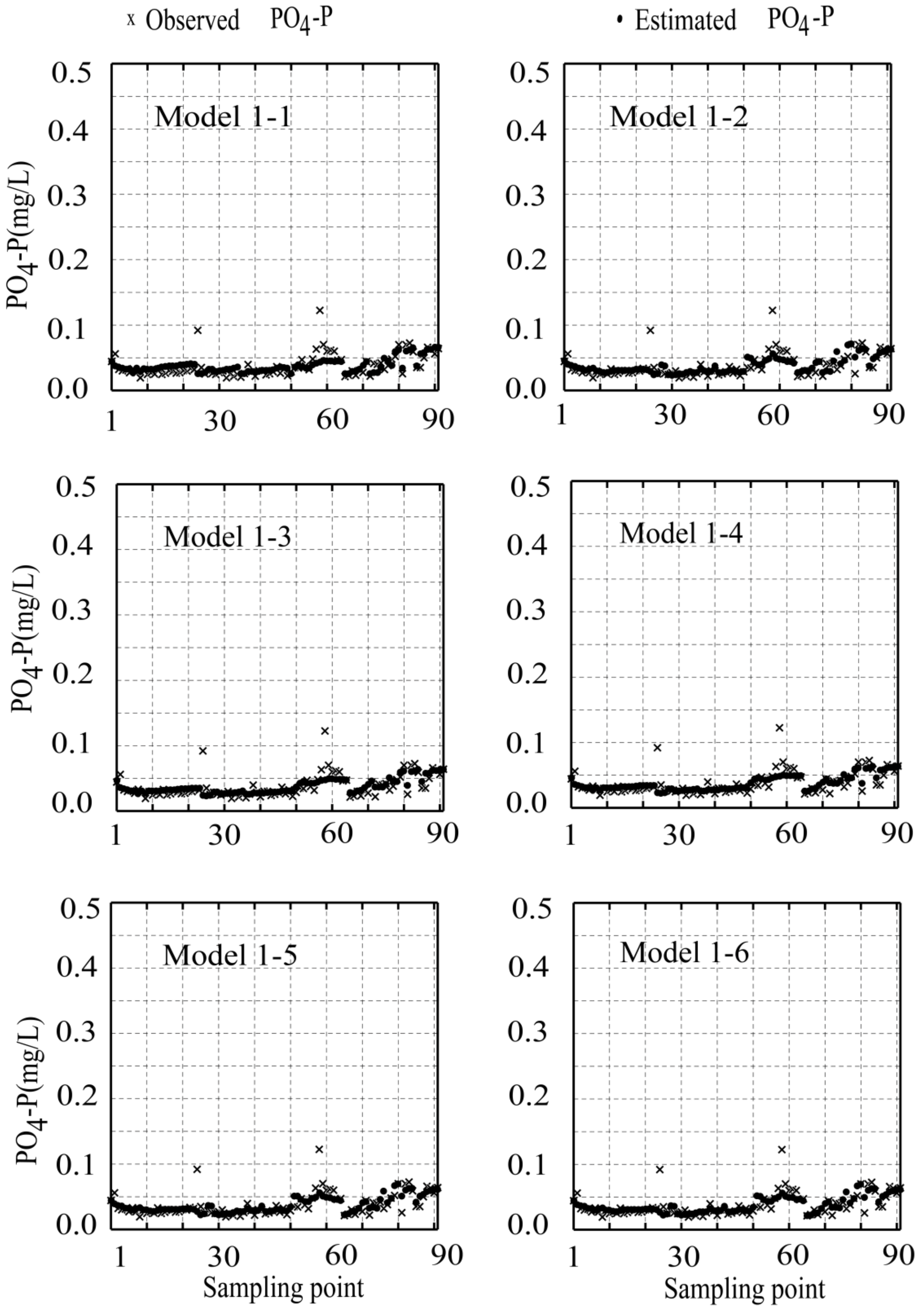

Figure 4.10: Observed and estimated PO_4-P concentration during the non-irrigation period for Model 1

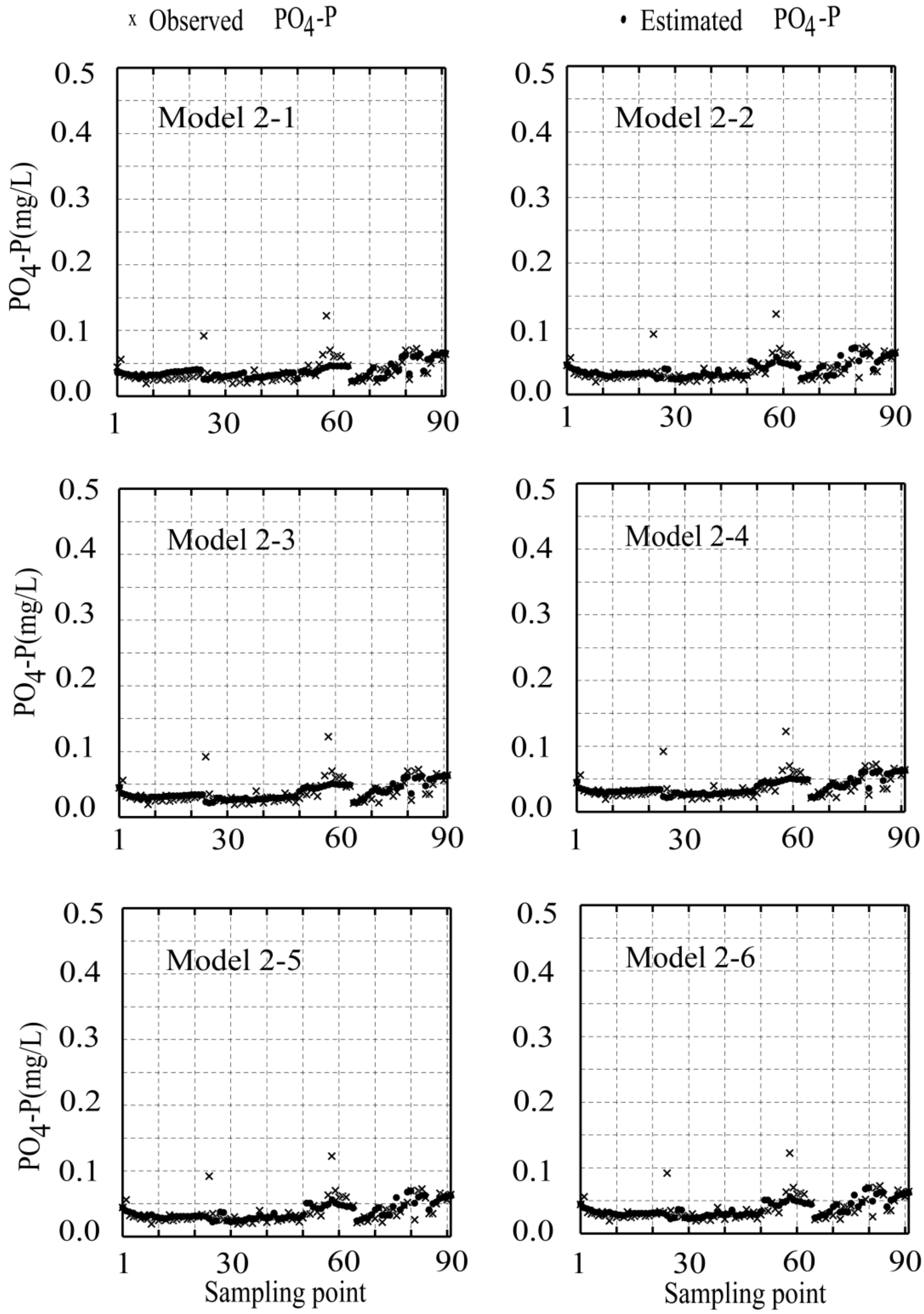

Figure 4.11: Observed and estimated PO_4-P concentration during the non-irrigation period for Model 2

pollutants. Increasing explanatory variables depicts better results in scenarios 5 and 6 for both irrigation and non- irrigation period.

4.4 Conclusion

This study investigated the temporal and spatial distribution of PO_4-P concentration in the Sengari Reservoir basin and formulated linear multiple regression models. PO_4-P concentration was considered as the response variable in the model, while land-use was used as the explanatory variable. The analysis was conducted during annual, irrigation, and non-irrigation periods. The model results revealed paddy fields and residential areas as the major pollutants in the reservoir, as they exhibited high values for their correlation coefficients, especially when compared to the low values found in forest areas. Golf courses had negative coefficients, and as a result, were not considered to be a pollutant source in the reservoir.

The irrigation period had higher coefficients than the non-irrigation period. Subbasins with septic tanks had positive coefficients, thus representing a pollutant source in the basin, while sewage treatment plants, possessing negative coefficients, act as an additional pollutant purification source. Evaluation of the models indicated better performance as the explanatory variables increased. The non-irrigation period had the best performance based on the AIC—the measured values depict the best trend due to reduced land-use activities during that time.

The models can be utilized in decision-making for land-use development in the basin. Using the estimated coefficients, different land-use scenarios can be modeled to see how they affect the PO_4-P concentration in the basin. Through this process, important information can be derived regarding effective ways to mitigate the adverse effects of water pollutants derived from the activities of different land-uses. In an effort to reduce eutrophication in the Sengari Reservoir basin, countermeasures such as the optimization of fertilizer application should be considered in paddy fields during the irrigation period to reduce the excessive application of nutrients that ultimately find their way into the reservoir.

CHAPTER 5

Assessing the Impact of Land Cover Change on Phosphate Phosphorus Load in the Hatsuka River Basin

5.1 Introduction

Water quality and quantity at both local and regional scales are influenced by global environmental change which is induced by natural variability of human activities (Chang, 2004). At a local level, land-use land cover change (LULCC) has been acknowledged as one of the most important anthropogenic disturbances to the environment. Modification of land-use through agriculture, forestry, urbanization have a profound effect on the functioning of the landscape and the general ecosystems (Gibson *et al.*, 2018). Effects of land cover change have profound effect on climate, soil quality, biodiversity and the ability of biological systems to sustain human needs (Samie *et al.*, 2017).

Nutrients transport and delivery are widely influenced by land cover changes and plays a significant role in water quality degradation. Phosphorus for instance is an essential fertilizer element enhancing plant growth. The global phosphorus-based food production has been vital for the estimated three-fold increase water quality degradation in the past 45 years (Couture *et al.*, 2014). Negative consequences as a result of increased nutrients in water is eutrophication which has given rise to harmful algal blooms that have many negative consequences on aquatic life and general livelihood (Couture *et al.*, 2014). Although both nitrogen and phosphorus contribute significantly to eutrophication of water bodies, phosphorus is usually the limiting factor for accelerated eutrophication because algae can utilize the abundant nitrogen available. Controlling phosphorus input from non-point source to surface water is therefore important in minimizing effects of eutrophication (Zhang *et al.*, 2003).

Understanding land cover changes is one of the most important tools for land planning decision making at both local and regional scale. To understand the uncertainties of land process under a range of possible futures and impact of interactions under changing environment, development of LULCC scenarios can be of great importance (Armenteras *et al.*, 2019). To understand the dynamics of many natural systems, spatial models are critical in developing hypothesis, making predictions and evaluating land-use trajectories (Armenteras *et al.*, 2019).

The interest in the application of computational approach in the study of human systems has expanded due to development computer-based modeling and analysis tools. They are being used to address various challenges and develop methodologies within human environment that seeks computational solutions with both numeric and symbolic data (Parker *et al.*, 2003). The focus of scientific studies across multiple disciplines, location and scale has been the understanding of many factors influencing LULCC. One of the comprehensive approach in understanding land cover change impact is linking observations at a range of spatial and temporal scale to empirical models (Parker *et al.*, 2003).

This study is conducted in the Hatsuka River basin which drains into the Sengari Reservoir. The aim of the study is to investigate the effect of land cover change on phosphate phosphorus (PO_4-P) load by conducting land cover change scenario testing in the basin.

5.2 Methodology

5.2.1 Study area

This study is applied in the Hatsuka River which is located in Hyogo Prefecture, Japan. It is the biggest river that drains into the Sengari Reservoir. Figure 5.1 shows the location of the study area. A steep undulating topography characterizes the basin. Dominant land-use in the watershed includes forest, paddy field, and residential area. Dominant soil in the basin consists of grey low land soil, brown forest soil, regosols, and lithosols.

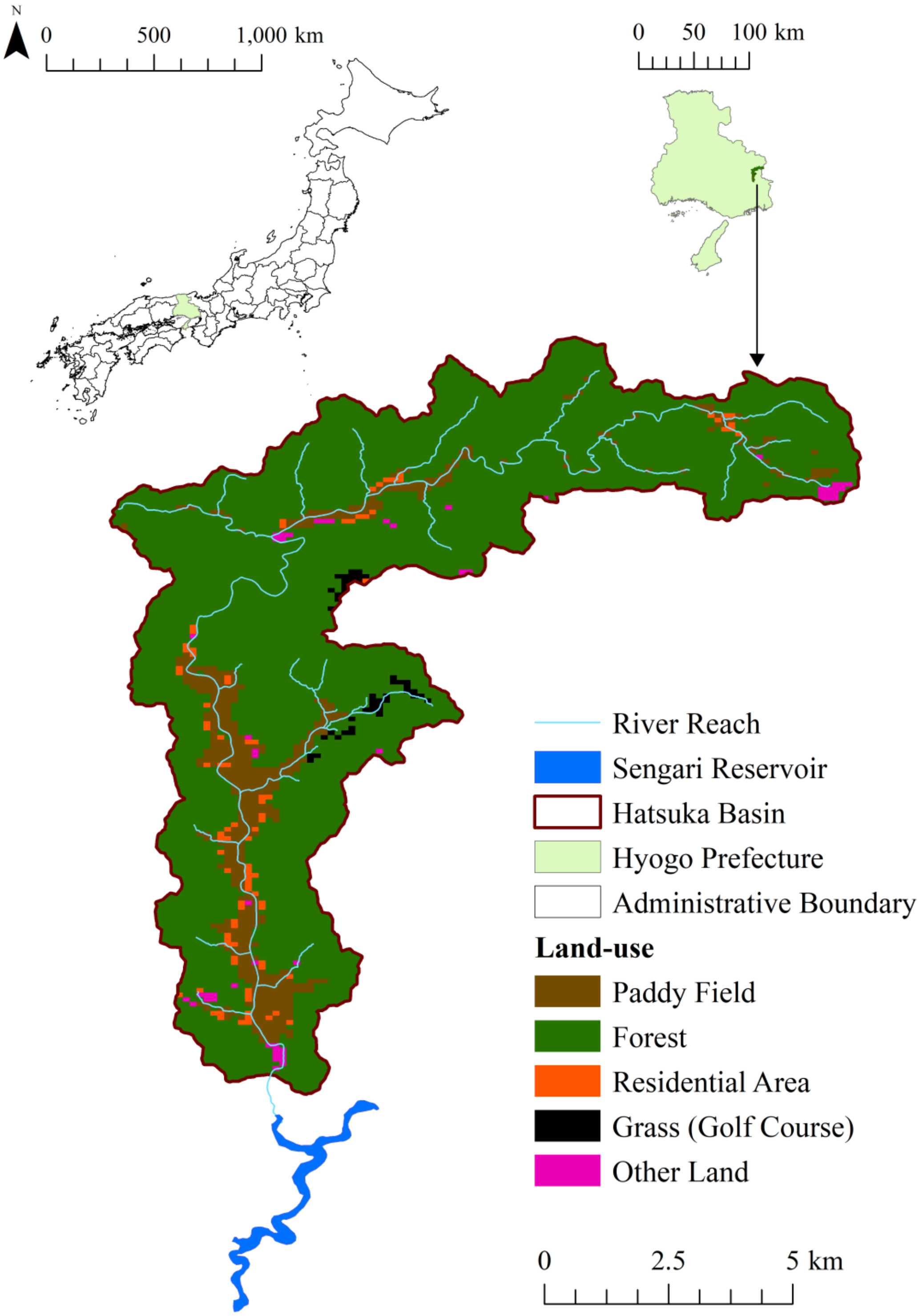

Figure 5.1: Study area and land-use

5.2.2 Water quality predictive model and scenarios

Linear regression water quality predictive model shown in Equation (5.1) was adapted to estimate PO_4-P load in the Hatsuka River basin. Partial correlation coefficient determined by Kimengich *et al*. (2019) are utilized to estimate PO_4-P concentration in the basin.

$$c = \sum \beta_i X_i \tag{5.1}$$

where c is the concentration of PO_4-P, β_i are the regression coefficients, and X_i $(= A_i / A)$ are the explanatory variables. A is the catchment area of the sampling point, and the subscript i ($\in$ {forest, paddy field, residential area, golf course, subbasin area of the sampling point}). This model estimates PO_4-P concentration based on land-use area in the catchment which was essential in determining PO_4-P load in the basin. Different land-use scenarios were evaluated on the Hatsuka River basin. According to the National Institute of Population and Social Security Research (2017), Japan is experiencing a sharp decline in population based on the projections. Therefore, possible scenarios as a consequence of declining population are tested in the Hatsuka River basin on how they influence PO_4-P load. With the Hatsuka River basin having relatively small catchment area, the following scenarios are tested:

- Conversion of 10% of paddy field to grass land (PO_4-P management scenario for abandoned land)
- Conversion of 50% of paddy field to grass land (PO_4-P management scenario for abandoned land)
- Converting residential areas to grass land (PO_4-P management scenario for abandoned land)
- Converting residential areas to paddy field ((PO_4-P management scenario for agriculture intensification)

The scenarios are evaluated based on annual PO_4-P load in the Hatsuka River basin after determining non-point pollution from different sources.

5.3 Results and discussions

5.3.1 Non-point source

The model relates land-use area with the calculated coefficient for prediction of PO_4-P load. Table 5.1 shows different land area and annual coefficients adopted. It can be seen that in the Hatsuka River basin, forest occupies the largest area in the basin followed by paddy fields, residential area and finally golf course. Average annual discharge considered in the estimation of PO_4-P load was 1.99 m^3/s as observed in the Hatsuka River basin.

Forest is the biggest contributor of pollutant load in the basin (49%) followed by paddy field (45%) and finally residential areas (6%) as shown in Figure 5.2. This is due to the large quantity of land occupied by the forest and relatively small area occupied by residential areas in the basin. Runoff from forested areas contributes to soil erosion that transport phosphorus load downstream to water sources. Forest being the dominant land-use in the Hatsuka River basin is serves as a significant source of pollution. Management of phosphorus load in the basin is subject to forest conservation practices to minimize erosion and increase runoff retention time for infiltration of nutrient load to occur. This can be done by ensuring maximum ground cover in forested areas to minimize exposure of soil surface.

Table 5.1: Land cover area and coefficients used

	Area (km^2)	Coefficients
Forest	53.09	0.055
Paddy field	5.642	0.473
Residential	0.916	0.377
Grass land (Golf course)	0.462	-0.014
Subbasin area	60.67	-0.049

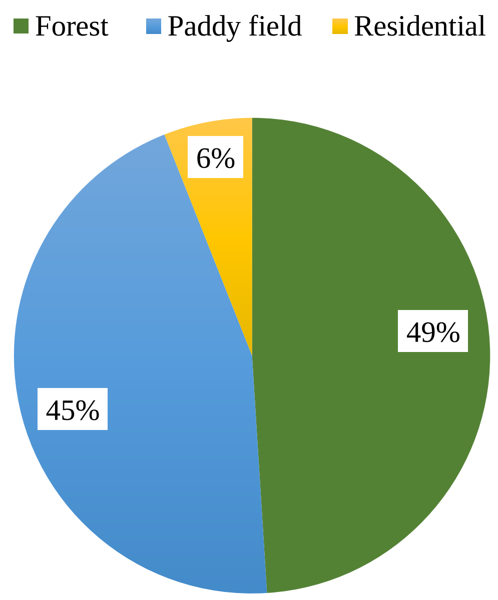

Figure 5.2: PO_4-P load from different sources

One of the leading sources of phosphorus load in contributing to eutrophication is agriculture (Al-Wadaey *et al.*, 2012). Nutrient load in paddy-field effluent have substantial impacts on downstream ecosystems (Hama *et al.*, 2013). Prior to introduction of inorganic fertilizers in paddy fields, when organic fertilizers and animal manure were utilized, the paddy field was useful for purification of water quality in Japan (Kaneki, 2003). After World War II, there was a decline in the amount of organic fertilizer used and an increased use of chemical fertilizers which lead to generation of effluent load making paddy fields a source of water pollution (Kaneki, 2003). Even though paddy field occupies a relatively small area in the Hatsuka River basin compared to forests, it is considered as one of major pollutant source in the basin.

Residential areas characterized by pavements and impervious surfaces. This leads to a decrease in water infiltration and an increase surface runoff. Lag time which is the time difference between the peak of precipitation volume to the peak of runoff volume, in shortened in urban catchments due to impervious surface (Paul and Meyer, 2001). Consequences of urban lands in ecosystem degradation includes the increased frequency and intensity of flood flows, decreased groundwater levels, increased stream bank erosion, and increased loads of pollutants (Hatt *et al.*, 2004). In the Hatsuka River basin, residential areas occupies a small percentage of area but it is also critical for pollutant load control.

5.3.2 Scenario testing

Land abandonment and agricultural intensification has altered traditional agricultural landscape in rural areas which largely affects biodiversity. To develop strategies to mitigate negative effect of land abandonment, future scenarios of land-use change with depopulation (Ohashi *et al.*, 2019) as encountered in the Hatsuka River basin are important. Table 5.2 shows the annual estimated load and resultant load after different scenarios are applied. Figure 5.3 shows the percentage change in annual load as a result of land-use change scenarios. Altering land cover has several effects in PO_4-P load in the Hatsuka River basin. Converting land 10% and 50% of agricultural land to grass land decreases PO_4-P load by 9% and 46% respectively. Converting residential area to grass land leads to a 12% decline in PO_4-P load while converting residential areas to paddy field under agricultural intensification scenario leads to a 2% increase in PO_4-P load.

When agricultural and residential area are converted to grass lands, there is a major decline in PO_4-P load in the basin. Grass land is considered as a PO_4-P reduction scenario for land utilization after abandoning. Grass land intercept runoff from the area and is significant in reducing non-point source load in water bodies. They remove sediments, and dissolved nutrients from surface runoff. This is enhanced by the ability of grass land to reduce velocity of runoff hence increasing nutrient uptake to the plant tissue as well as increasing deposition through interception of soil sediments. It also promotes the degradation sediment bound chemicals (Blanco-Canqui *et al.*, 2004; Mankin *et al.*, 2007; Al-Wadaey *et al.*, 2012). Therefore, total phosphorus retention is a result of physical trapping of fine sediments in conjunction with the use of to increase phosphorus uptake in plant tissues which is enhanced by high biomass produced by native grass (Mankin *et al.*, 2007).

Table 5.2: Annual average load from different scenarios

	PO_4-P load (kg/year)
Estimated	3048
10% Rice to grass	2765
50% Rice to grass	1631
Resident to grass	2692
Residential to rice	3139

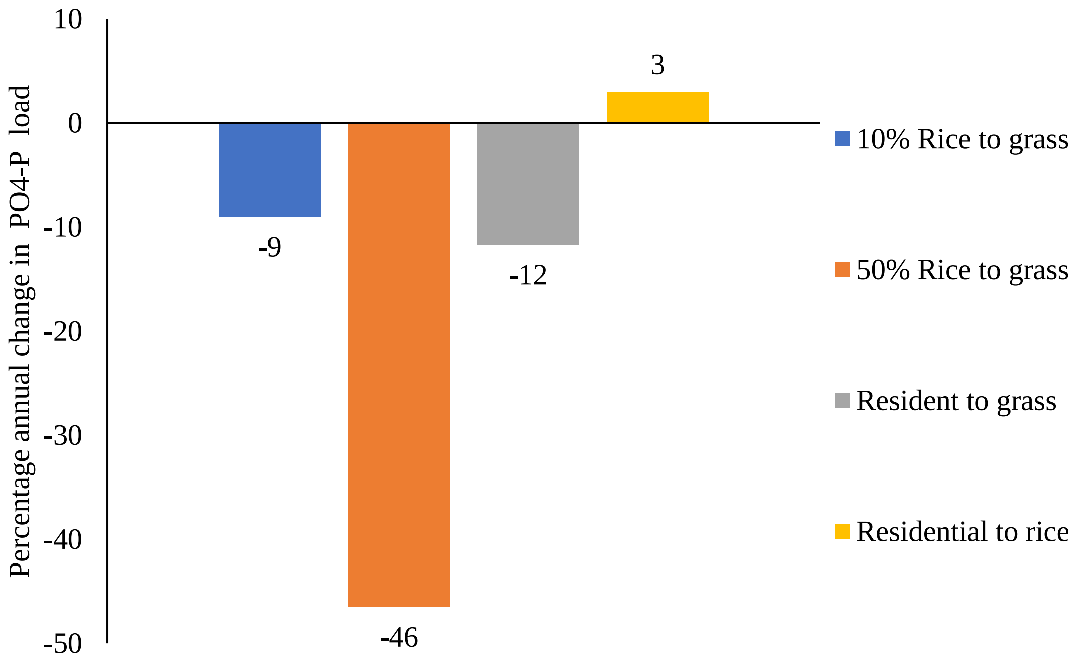

Figure 5.3: Change in PO_4-P load under different scenarios

When assuming residential area are converted to paddy fields for agriculture intensification, there is a resultant increase in phosphorus load in the basin. Thus, agricultural areas still exerted the strongest influence on total loading compared to residential areas. The percentage increase is relatively small because residential areas were already contributing to phosphorus load prior to the change. Significant changes may occur when previously non-contributing land are converted to paddy fields. The sequence in which land-use changes occur is important. Soranno *et al.* (1996) suggested that transitions from natural vegetation to land disturbed by either agriculture or urbanization may have the largest effects on total loading, especially when the changes occur in large proportions of the watershed. In the Hatsuka River basin however, most of the forested areas are located in mountainous areas that are both inhabitable and impossible to transform to paddy fields. Therefore, this scenario is likely not possible to occur in Hatsuka River basin.

5.4 Conclusion

This study estimated non-point source PO_4-P load from different sources and conducted land cover scenario testing on the Hatsuka River basin. The scenarios considered declining trend in population and abandoned paddy fields. PO_4-P reduction scenarios of converting a fraction paddy fields and residential areas to grass lands was evaluated. Agriculture intensification by converting residential areas to paddy field was also evaluated. The major contributor of PO_4-P load in the basin is forest as due to occupation of large percentage area of land. In regulation of phosphorus in the basin forest management as providing adequate soil cover is important to prevent erosion and runoff which transports phosphorus load downstream.

Converting paddy field and residential areas to grass land leads to decline in phosphorus load. This is as a result of the ability of grass land to protect the soil surface limiting runoff and increasing infiltration of phosphorus load. This serves as a recommendation for decreasing phosphorus load in the Hatsuka River basin in abandoned lands. Converting residential areas to paddy fields leads to a slight increase in load because residential areas are already a contributing factor under the current conditions.

Management of phosphorus load in the Hatsuka River basin is subject to decision making on proper utilization and management of abandoned land, paddy fields and forest management.

CHAPTER 6

Modeling Non-point Source Phosphorus Load on a Rural Basin with OWTS

6.1 Introduction

This study was conducted in the Hazu River basin where sources of non-point source (NPS) pollutants include forest, agricultural field and residential areas where septic tanks, which are the main onsite wastewater treatment systems (OWTS), are utilized for treating domestic wastewater. OWTS are important NPS pollution sources in rural areas, and their effect should be quantified. The average removal ratios of conventional septic tanks designed for less than 10 people is 28% for total nitrogen (TN) and 16% for total phosphorus (TP) (Fujimura, 2006). Nutrient flux from a single septic tank is small, but their cumulative effect is significant at the watershed scale (Haruta and Sakurai, 2010; Withers *et al.*, 2011; Shimizu *et al.*, 2015). Several studies have linked surface water pollution caused by phosphorus contamination derived from septic systems (Lusk *et al.*, 2011). It is therefore important to consider their effect in the watershed.

Forest and agricultural areas are also critical NPS pollution sources. In Japan, loads from forested mountains as a significant source of phosphorus have become an issue in recent years because the quality of public waters has not sufficiently improved (Takeda, 2001). Heavy rainfall generates flood and consequently induce massive nutrient loss from the forested mountains. Agricultural lands contribute largely to phosphorus loads due to operational activities that escalate surface water pollution. This includes the application of fertilizers, pesticides, irrigation, cultivation, among others that influence load transportation to water sources directly and indirectly.

Water quality impairments from NPS can be mitigated by taking several measures. One method is the development of total maximum daily loads. This method determines pollution sources within a watershed and allocates acceptable levels of pollution to each source (White *et al*., 2014). This can be facilitated by adopting computer models that make it easier to carry out the analysis on a spatial scale. Computer models are useful in evaluating the mechanisms that govern nutrient sources, transport, and delivery from watersheds to lakes and reservoirs (Migliaccio *et al*., 2007). Models, coupled with observational data from historical and current monitoring programs, provide the information for load allocations and implementation strategies (Santhi *et al*., 2002).

Distributed catchment models are adapted to represent the spatial description of many physical processes involved in phosphorus removal from the catchment and their transportation (Nasr e*t al*., 2004). These models simulate landscape processes, which result in nutrient delivery to water bodies and lotic nutrient cycling and transformations, which occur in streams and rivers (White *et al*., 2014).

Many distributed models encounter limitations for NPS pollution simulation such as inappropriate scaling, inability to perform continuous-time simulation, inadequate maximum number of subareas generated, and inability to characterize the watershed in enough spatial detail. Therefore SWAT model was developed to provide continuous-time simulations incorporating a high level of spatial information (Saleh *et al*., 2000). It is one of the most utilized water quality and hydrological models, having a long history of model development (Gassman *et al*., 2014). In simulating the effect of OWTS, Jeong *et al*. (2011), incorporated the biozone algorithm by Siegrist *et al*. (2005), into the SWAT model. The logarithmic representation describes biozone process validated at watershed scale and its coefficients calibrated at experimental field data (Neitsch *et al*., 2011). This is useful in understanding the effect of OWTS at watershed scale on various nutrient loads.

Modeling water and nutrient dynamics at the watershed scale is an indispensable approach to solving water resource issues and maintaining the water environment in the future. The objective of this study is to apply SWAT model for simulation of discharge and phosphorus load in the Hazu River basin, quantify phosphorus load generated from different land-use and assess the effect of OWTS on phosphorus load in the basin.

6.2 Methodology

6.2.1 Phosphorus in SWAT model

Mineral soils have three significant forms of phosphorus: organic phosphorus from humus, insoluble mineral phosphorus, and plant-available phosphorus in soil solution. SWAT monitors six different pools of phosphorus in the soil. Three pools are inorganic forms of phosphorus while the other three are organic as shown in Figure 6.1. Fresh organic phosphorus is associated with crop residue and microbial biomass while the active and stable organic phosphorus pools are associated with the soil humus. The organic phosphorus associated with humus is partitioned into two pools to account for the variation in the availability of humic substances to mineralization. Soil inorganic phosphorus is partitioned into solution, active, and stable pools. The solution pool is in rapid equilibrium (several days or weeks) with the active pool (Neitsch *et al*., 2011).

The process of microbial conversion of organic phosphorus to inorganic, plant-available phosphorus is conducted through mineralization and the breakdown of organic molecule to simpler product is carried out through decomposition. The fresh organic phosphorus pool associated with crop residue and microbial biomass and the active organic phosphorus pool associated with soil humus are the sources considered for mineralization. Mineralization and decomposition are dependent on water availability and temperature. Solution phosphorus concentration decreases rapidly with time due to reaction with the soil after an application of soluble phosphorus fertilizer. To account for the initial rapid decrease, SWAT assumes a rapid equilibrium exists between solution phosphorus and active mineral phosphorus. The subsequent slow reaction is simulated by the slow equilibrium which is assumed to exist between the active and stable mineral pools. The equilibrium between the solution and active mineral pool is governed by the phosphorus availability index (Neitsch *et al*., 2011).

Different approaches evaluate the phosphorus movement within the catchment. First, soluble phosphorus is allowed to leach from 10 mm of soil into the first soil layer. Due to the low mobility of phosphorus, SWAT allows soluble phosphorus to leach only from the top 10 mm of soil into the first soil layer. Surface runoff carries organic and

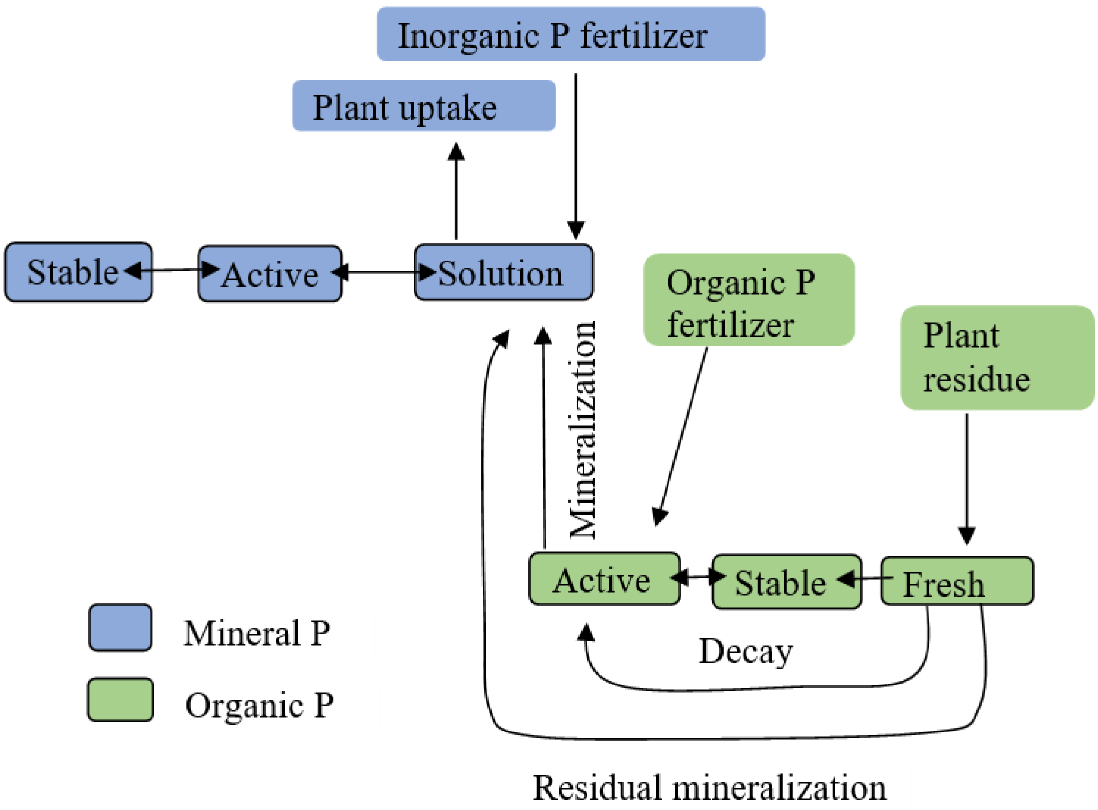

Figure 6.1: Soil phosphorus pools simulated by SWAT model

mineral phosphorus attached to soil particles to the main channel in SWAT. Simulation of erosion and sediment yield are conducted with the modified universal soil loss equation (Williams, 1995). Loading function developed by McElroy *et al*. (1976) and modified by Williams and Hann (1978), calculates the amount of phosphorus transported with sediments to the main channel.

6.2.2 Study area and datasets

The Hazu River basin is a predominantly rural area located in Hyogo Prefecture, Japan. It has a total length of about 10 km with a basin area of about 25 km². It drains into the Sengari Reservoir which supplies domestic water Kobe City. A steep undulating topography characterizes the basin. The main land-use in the watershed includes forest, agricultural land, and residential areas. Dominant soil consists of grey low land soil,

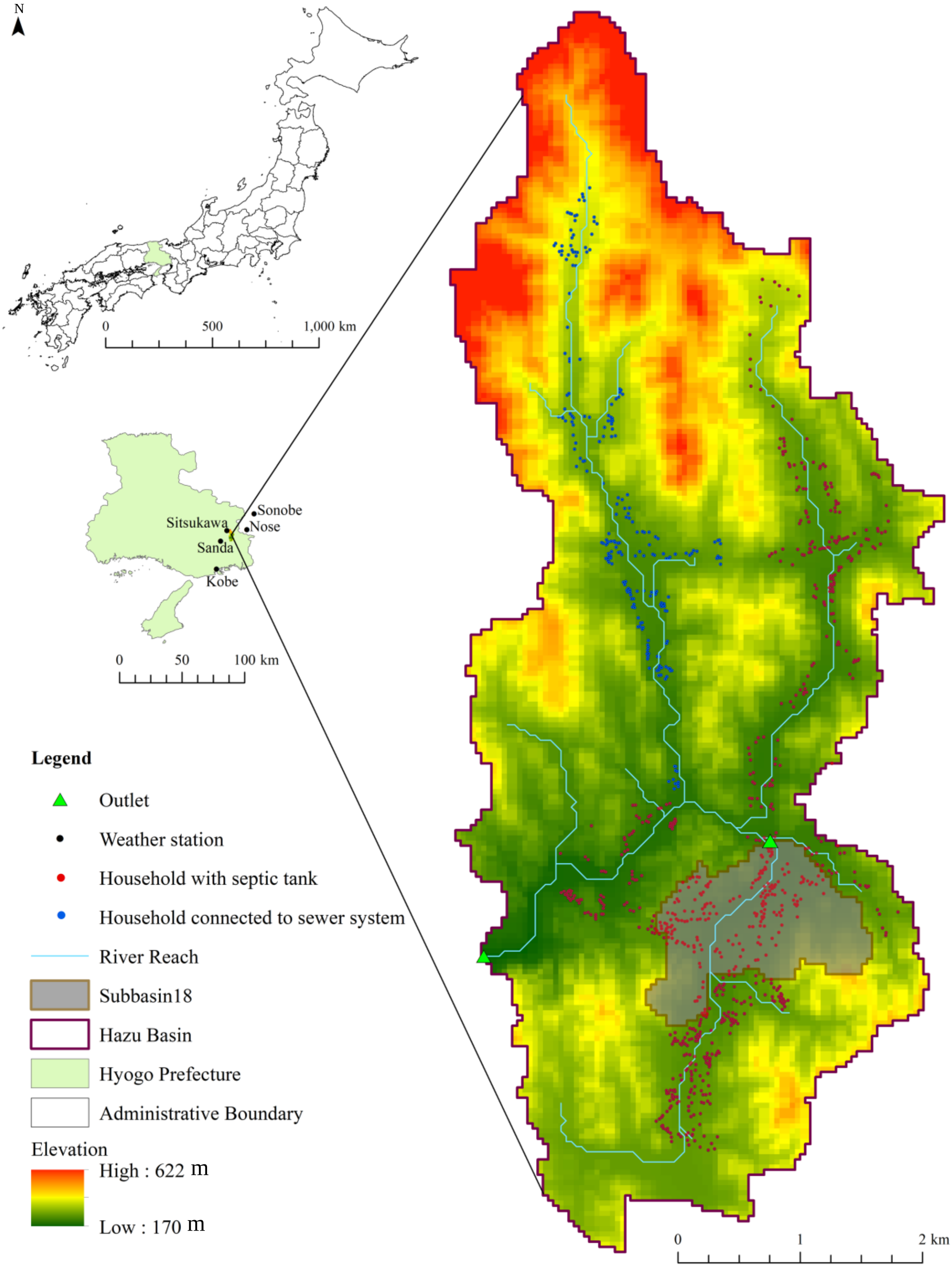

Figure 6.2: Location of Hazu River basin and Subbasin 18

brown forest soil, regosols, and lithosols. Currently, a small portion of households are connected to sewer system in the Hazu River basin for domestic wastewater treatment. Majority of the households are therefore fitted with OWTS for wastewater treatment. Figure 6.2 shows the location of the study area, stream network, elevation and household distribution in the basin.

Spatial datasets used in the model includes the Digital Elevation Model (DEM), land-use, and soil data from Ministry of Land, Infrastructure, Transport and Tourism. DEM delineates the watershed and subbasins covering the entire process of flow direction, flow accumulation, and stream network generation. Temporal datasets comprise of climatic data, discharge and TP load from the year 2006 to 2015. Climate data includes precipitation, temperature, humidity, wind and solar radiation. Five stations serves as the source of climatic data. These included Sanda, Nose, Kobe, Shitsukawa, and Sonobe. The data are obtained from Automated Meteorological Data Acquisition System (AMeDAS) of Japan Meteorological Agency. Discharge and TP load data are obtained from Water Quality Examination Laboratory, Kobe City Water Works Bureau. These data are used for model simulation, calibration, and validation.

6.2.3 Simulation

ArcGIS 10.4 is used as an interface to run SWAT 2012 model. The basin is sub-divided into 22 subbasins with different hydrologic response units (HRUs). Households in the rural settlement are digitized. Since major parts of the wastewater is treated with septic tanks in the Hazu River basin, the underlying assumption is that each household not connected to the sewer system represented a septic tank. This would enable the estimation of the effect OWTS within the basin. Digitized point data was converted to raster with an area of 100 m^2 representing the septic tank drain fields (Hoghooghi *et al.*, 2017), and merged with the land-use data. Distance from septic tank to the stream was determined using near distance toolbox in ArcGIS. Initial TP concentration in the septic tank is10 mg/L. The number of residents in each house is set as 2.3 according to the Japan statistics report (Statistics Bureau, 2019). Automatic irrigation and fertilizer application are incorporated in agricultural fields based on crop demand during the cultivation period.

The simulation period ranges from 2006 to 2015, inclusive of a 3-year warm-up period. Calibration is conducted using SWAT Calibration and Uncertainty Program (CUP) with parameters selected from sensitivity analysis. The model is run with the presence and absence of OWTS to evaluate their effect on TP contribution. A comparison was made between the watershed outlet and Subbasin 18 outlet, which has the highest number of septic tanks.

Uncertainty Fitting Algorithm (SUFI-2) is used as the optimization program for model calibration and validation. SUFI-2 accounts for all sources of uncertainty, such as conceptual model, input parameters, driving variables, and measured data. Uncertainties in the parameters result in the model output uncertainties, which are quantified by the 95% prediction uncertainty (95PPU) band between the 2.5% and 97.5% levels of the cumulative distribution of an output variable using Latin hypercube sampling envelope (Abbaspour, 2015). The 95PPU is measured by P and R-factors. P-factor is the percentage of data incorporated in the 95PPU. While R-factor is the range of 95PPU band. In an ideal situation, P-factor should incorporate 100% of the data. The calibration period ranges from 2009 to 2012, and the validation period is from 2013 to 2015.

6.2.4 Model evaluation

The model efficiency is evaluated by the coefficient of determination (R^2), Nash-Sutcliffe (NS) test and PBIAS, as shown in Equations (6.1), (6.2) and (6.3). This determines the effectiveness of the model by comparing the results based on simulated and observed data.

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(\left(O_i - O_{avg}\right)\left(P_i - P_{avg}\right)\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - O_{avg}\right)^2 \sum_{i=1}^{n}\left(P_i - P_{avg}\right)^2} \tag{6.1}$$

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum_{i=1}^{n}\left(O_i - O_{avg}\right)^2} \tag{6.2}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \qquad (6.3)$$

where O_i is the observed data on day i, O_{avg} is average of observed data, P_i is simulation data on day i and P_{avg} is average of simulation data.

6.3 Results and discussions

6.3.1 Calibration and validation

Sensitive parameters used for calibration and validation of hydrological variables included, Soil Conservation Service runoff curve number (CN2), the exponential decay factor for groundwater flow to the stream (ALPHA_BF) (days), the groundwater re-evaporation coefficient (GW_REVAP), initial depth of water in the deep aquifer (DEEPST) (mm), deep aquifer percolation fraction (RCHRG_DP), effective hydraulic conductivity of the alluvium in the main channel (CH_K2) (m/s), the Manning's coefficient for the tributary channels (CH_N1), soil evaporation compensation factor (ESCO), available water capacity of the soil layers (SOL_AWC) and average slope steepness (HRU_SLP). Parameter ranges and fitted values are shown in Table 6.1.

Parameters used for phosphorus calibration included phosphorus percolation coefficient (PPERCO) (m^3/Mg), phosphorus soil partitioning coefficient (PHOSKD) (m^3/Mg), phosphorus sorption coefficient (PSP), phosphorus uptake distribution parameter (P_UPDIS), organic phosphorus enrichment ratio (ERORGP), rate constant for mineralization of organic phosphorus to dissolved phosphorus in the reach (BC4), benthic (sediment) source rate for dissolved phosphorus in the reach (RS2) ($mg/m^2/day$), and organic phosphorus settling rate in the reach (RS5) at 20˚C (day^{-1}).

Parameters used for sediment calibration included, peak rate adjustment factor for sediment routing in the main channel (PRF_BSN), peak rate adjustment factor for sediment routing in the subbasin (ADJ_PKR), linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing

Table 6.1: Parameter range and fitted values used for model calibration

Parameter Name	Minimum value	Maximum value	Fitted Value
RCHRG_DP	0.0500	1.0000	0.1816
CN2 Forest	35.000	98.000	80.000
CN2 Rice	35.000	98.000	75.000
CN2 Resident	35.000	98.000	72.000
ALPHA_BF	0.0500	1.0000	0.2832
SOL_AWC	0.0000	1.0000	0.3000
GW_REVAP	0.0200	0.2000	0.0548
CH_K2	1.0000	500.00	306.13
DEEPST	0.0000	5000.0	2311.0
ESCO	0.0000	1.0000	0.8675
HRU_SLP	0.0000	1.0000	0.2665
CH_N1	0.0100	0.5000	0.4184
PPERCO	10.000	17.500	13.3787
PSP	0.0100	0.7000	0.5768
PHOSKD	100.00	200.00	164.44
P_UPDIS	0.0000	25.000	13.962
ERORGP	0.0000	5.0000	0.0475
BC4	0.0100	0.7000	0.0469
RS2	0.0010	0.1000	0.0335
RS5	0.0010	0.1000	0.0130
PRF_BSN	0.0000	2.0000	1.8470
ADJ_PKR	0.5000	2.0000	0.7662
SPCON	0.0001	0.0100	0.0013
SPEXP	1.0000	1.5000	1.1793
CH_COV1	-0.0500	0.6000	0.2786
CH_COV2	-0.0010	1.0000	0.7733
LAT_SED	0.0000	5000.0	3282.5

(SPCON), exponent parameter for calculating sediment re-entrained the in channel (SPEXP), sediment routing channel erodibility factor (CH_COV1), channel cover factor (CH_COV2), and sediment concentration in lateral flow and groundwater flow (LAT_SED) (mg/L).

Simulated discharge load and TP are compared with observed data and evaluated with the performance criteria. Table 6.2 shows the model performance evaluation and uncertainty analysis results. According to SWAT model evaluation guidelines by Moriasi *et al*. (2007), when NSE ≥ 65 ≤ 75, the results are termed as "good". NES ≥ 75 is considered "very good". Figures 6.3 and 6.4 show the average monthly trend between observed and simulated discharge while Figures 6.5 and 6.6 depict observed and simulated TP load at the outlet. Slight deviations between the simulated and observed discharge data may be due to the model limitation in precipitation representation and other conceptual uncertainties in the model. SWAT model determines the spatial distribution of rainfall by interpolation technique which cannot represent irregular distribution and magnitude across the watershed (Shen *et al*., 2013; Kimengich *et al*., 2018). Deviation in TP load between observed and simulated data is as a result of complexity in the generation, fate and transportation of the load which is affected by hydrology and other land characteristics (Eckhardt *et al*., 2003; Shen *et al*., 2012; Shen *et al*., 2013).

The average monthly simulation of TP load was under-predicted by 7%. The average annual prediction of TP was 2,332 kg compared with 2,569 kg of observed load. This was slightly under-predicted by 6%. The highest amount of load was generated in 2010 and 2011 as shown in Figure 6.7, due to a large amount of precipitation received which in turn increased total discharge in the river outlet. The lowest amount of TP load was in 2009 and 2012 which received little precipitation compared to other years.

Table 6.2: Evaluation performance during calibration and validation period

	Discharge		TP load	
	Calibration	Validation	Calibration	Validation
NS	0.81	0.91	0.70	0.92
R^2	0.89	0.95	0.75	0.95
PBIAS	18.4	4.6	7.2	19.1
P-factor	0.67	0.81	0.73	0.64
R-factor	0.89	0.69	4.74	2.69

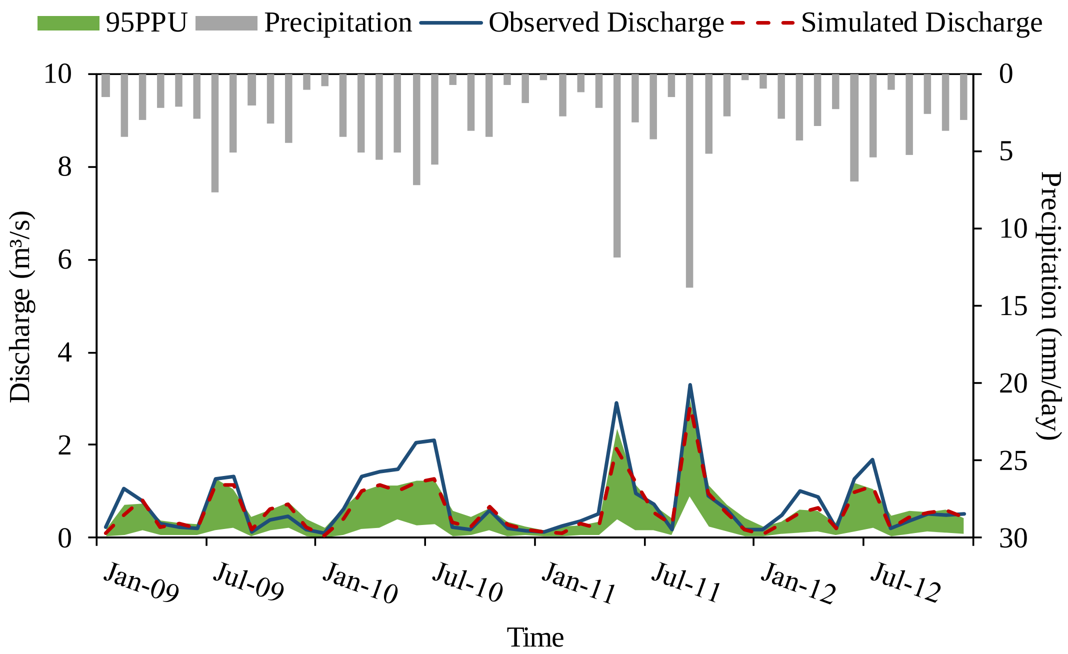

Figure 6.3: Observed and simulated discharge during calibration period at the basin outlet

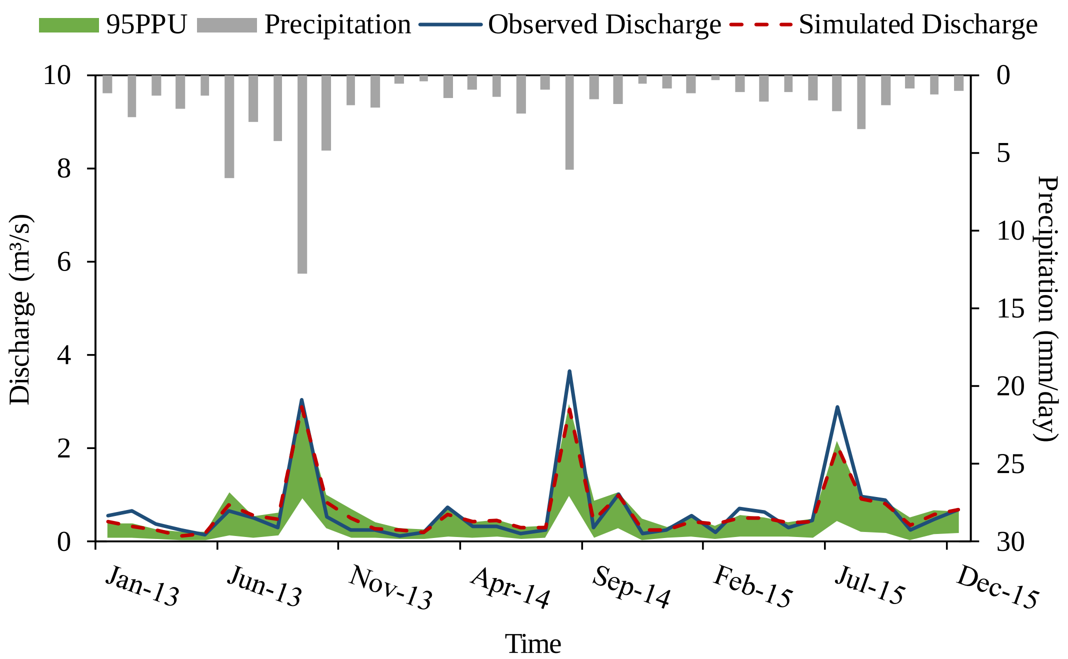

Figure 6.4: Observed and simulated discharge during validation period at the basin outlet

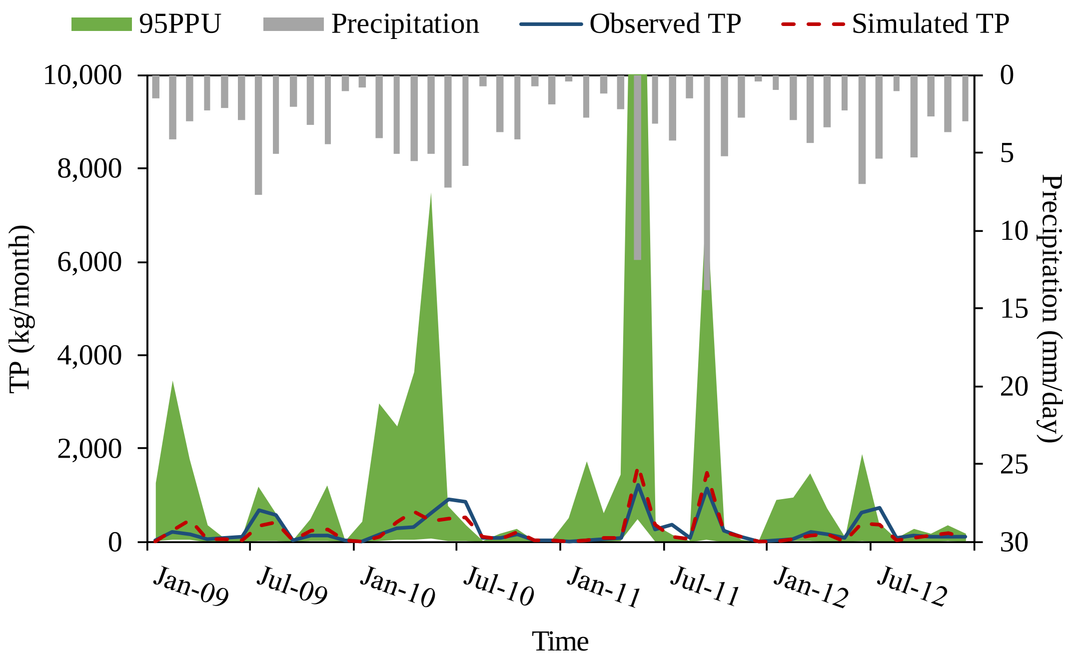

Figure 6.5: Observed and simulated TP during calibration period at the basin outlet

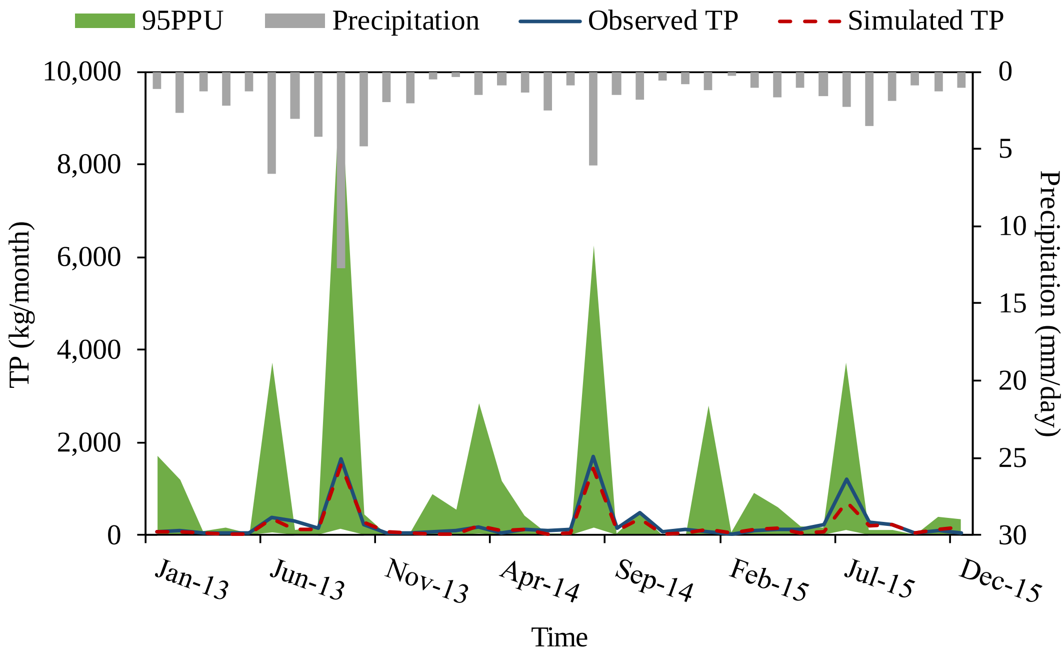

Figure 6.6: Observed and simulated TP during validation period at the basin outlet

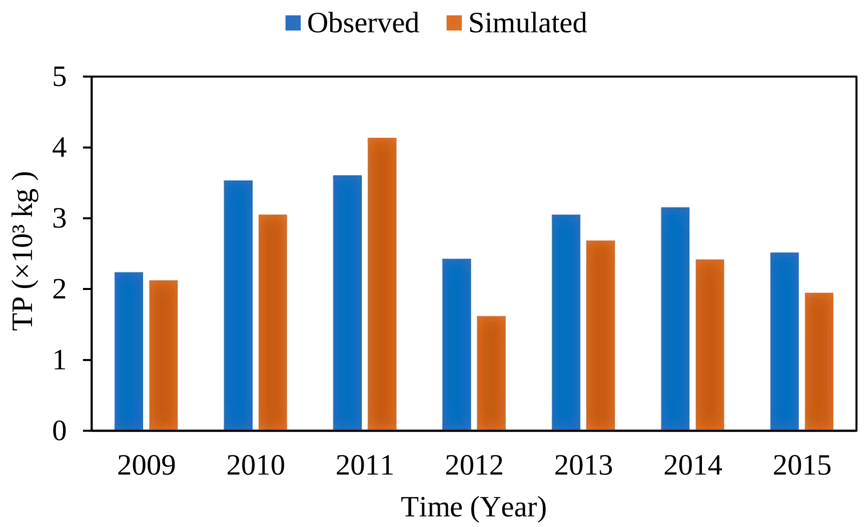

Figure 6.7: Annual TP load

6.3.2 NPS pollution load

Phosphorus load from NPS differs based on different land-use. Forestlands exhibited the highest amount of load (66%) because it occupies 80% of the total land area in the Hazu River basin, agricultural land accounted for 31% and residential areas 3% of the load generated. Figures 6.8 shows the percentage load generated from different land cover. For the load generated per unit area, agricultural land contributed 2.00 kg/ha, residential areas 0.88 kg/ha and finally forest 0.64 kg/ha.

Forest characteristics influence the type of load. Dominant phosphorus load from the natural forest is mainly dissolved phosphorus while particulate phosphorus dominates disturbed forest due to exposed soil surface which enhances high soil erosion (Hattori *et al*., 1992; Tachibana, 1993; Yukawa and Onda, 1995; Ide *et al*., 2007). Erosion by runoff enhances the transportation of phosphorus attached with sediment particles to downstream water bodies hence posing more threats compared to natural forest. Despite planted forest in Japan covering 41% of total forest area, Otsuki *et al*., (2001) reported insufficient management operation as forest pruning and thinning.

Agricultural influence on the watershed as one of the main sources of NPS pollution has been reported by other studies (Somura *et al*., 2012; Shen *et al*., 2013). Fertilizer containing phosphorus applied during high rainfall or irrigation period has the highest

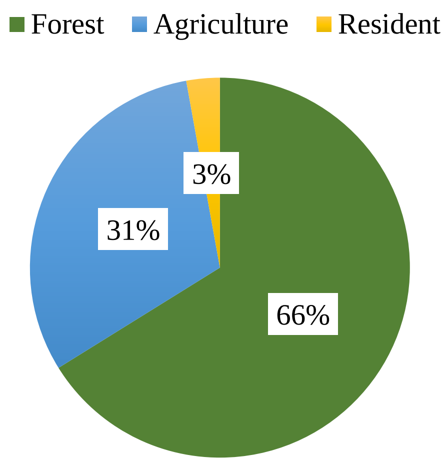

Figure 6.8: TP load contribution from different sources

transfer potential to water bodies (Nash *et al.*, 2000; Kleinman and Sharpley, 2003; Withers *et al.*, 2003).

The hydrologic controls in phosphorus transfer are location specific, varies with scale and are dynamic (Kleinman *et al.*, 2011). The spatial heterogeneity in phosphorus transferred from field to waterbody is influenced by variable source hydrology which is the variation runoff from different areas influenced by factors as slope and soil saturation (Walter *et al.*, 2000; Sen *et al.*, 2008; Srinivasan and McDowell, 2009), which dictates load transportation to water bodies in the basin.

6.3.3 Septic tank

The effect of septic tank is evaluated by comparing total phosphorus at the outlet of the basin and Subbasin 18 which is estimated to have the highest number of households. When septic tanks are replaced by the sewer system the results indicate about 0.2% decrease in phosphorus load at the basin outlet compared to 1.5% average annual decrease in Subbasin 18 outlet as shown in Figure 6.9. TP contribution from residential areas decreases by 6% at the basin outlet and 25% at Subbasin 18.

The results show that the influence of septic tanks on the basin is low in the watershed outlet compared to Subbasin 18 outlet. This is because of the small household percentage

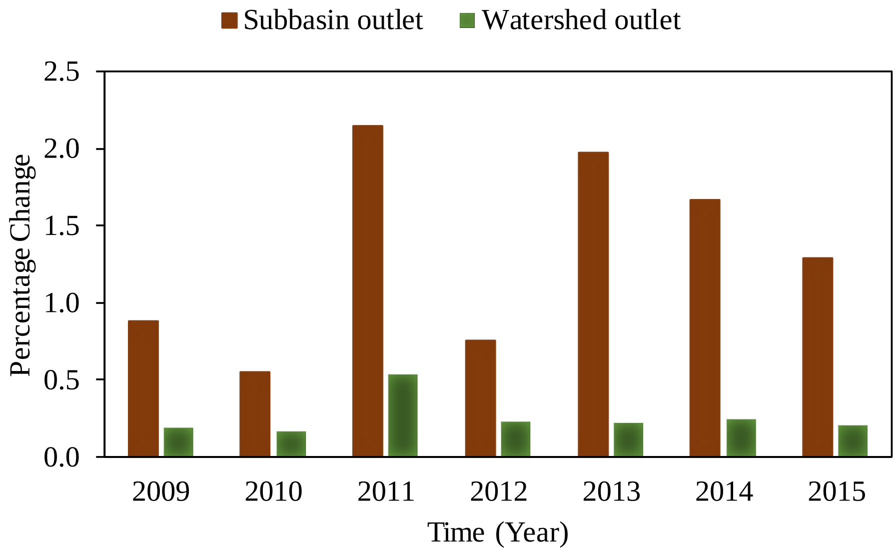

Figure 6.9: Change in TP load at the basin outlet and Subbasin 18 outlet due to the septic tank effect

in the watershed hence most of the load is emanated from other NPS sources as forest and agriculture. In modeling phosphorus transport the Blue River watershed, Lemonds *et al*. (2003) reported little influence of OWTS on phosphorus contribution in comparison to other NPS pollutants in the basin. In Subbasin 18, an increase in the average annual percentage is due to the increased density of septic tanks. In septic systems, phosphorus load is a concern as it can impair water quality at much lower concentrations in comparison to nitrogen. Surface waters can become eutrophic when the phosphorus concentration exceeds 0.02 mg/L (Lusk *et al*., 2011). Fujimura (2006) reported that the average concentration of domestic water effluent after treatment was 3.2 mg/L. Other studies have reported levels as much as 10 mg/L in septic tank effluent (Lusk *et al*., 2011). Kimengich *et al*. (2019) reported increased phosphorus load in the subbasins containing septic tanks in the Hazu River basin.

Most of the households are located in close proximity to the river. The average distance from septic tank to the stream in the Hazu River basin is about 170 m. This may decrease adsorption in the soil causing an increase in phosphorus concentration in the river. The most commonly recommended means of reducing phosphorus transport to surface water is to increase the distance from the OWTS to water bodies, thus increasing the chances for phosphorus adsorption (Lusk *et al*., 2011). Failure is septic systems caused by clogging can increase the amount of phosphorus concentration in the watershed causing severe impacts on water quality.

6.4 Conclusion

Discharge and TP load were simulated in the Hazu River basin and yielded relatively good performance based on NS, R^2, and PBIAS. There was a reasonable trend between the observed and simulated TP as they followed the precipitation regime. The average annual amount of TP load predicted in the watershed was 2,332 kg compared with 2,569 kg of the observed load.

Non-point source phosphorus load was estimated from different land-use. Forest areas accounted for the highest load generated in the entire watershed as they occupied the biggest portion of land in the basin followed by agricultural lands and residential areas. For load generated per unit area, agricultural land had the highest amount of load followed by residential areas and forests respectively. When septic tanks are replaced by the sewer system, TP load decreases by 1.5% at Subbasin18 outlet and 0.2% at the basin outlet. The proximity of septic tanks to the streams may be detrimental in septic tank failures and may increase phosphorus concentration.

Quantification of NPS pollutants is essential in the regulation and management of load from different land-use. Measures may be taken to control agricultural operation activities as optimization of fertilizer application to prevent excessive loss. Forest management is also an important consideration in preventing excessive phosphorus delivery to the Sengari Reservoir. Despite several uncertainties, SWAT model can be useful in providing insight in comprehending general hydrological and NPS pollution load in the basin. This will aid in carrying out the best operation management practice scenarios in the basin.

CHAPTER 7

Summation

7.1 Summary and conclusion

This thesis presents an elaborate application of hydrological and water quality modeling on rural watersheds. The uniqueness of different watersheds in terms of climate, land-use, soil, and hydrogeological configuration raises the curiosity for applying hydrological and water quality models in different areas to quantify their exclusive challenges.

In Chapter 3, SWAT model was applied in a highly managed watershed to simulate streamflow. Automatic irrigation from the reach is considered in paddy fields. Two reservoirs along the main channel were included in the model. Simulation period ranged from the year 1990 to 2009 inclusive of a two-year warm up period. Sequential Uncertainty Fitting Algorithm (SUFI-2) was used as an optimization program for model calibration, validation, parameter statistical significance and uncertainty analysis. Calibration was conducted from 1992 to 2000 whereas validation is from 2001 to 2009. The performance of the model was determined by coefficient of determination (R^2) and Nash-Sutcliffe (NS). SWAT provided a suitable platform for hydrological modeling of the Yasu River basin with relatively good performance for streamflow simulation.

In Chapter 4, a linear regressive water quality predictive model was developed and applied. The model tried to quantitatively investigate the PO_4-P load emitted from different land-uses in the basin by developing partial correlation coefficients. The model was applied in the Sengari Reservoir basin. Water was sampled at regular intervals along the rivers and analyzed to understand the temporal and spatial changes of PO_4-P concentration in the basin. A comparison was made between the irrigation and non-irrigation period, and subbasins with septic tanks and those with rural sewage treatment plants. Results from the linear regression models indicated that paddy fields and residential areas had the highest coefficients compared to forests and golf courses. The irrigation period had a high PO_4-P concentration compared to the non-irrigation period. Subbasins with septic tanks had a high PO_4-P compared to those with rural sewage treatment plants. Effectively managing water quality in the Sengari Reservoir to reduce eutrophication depends on significantly reducing the nutrients in agricultural areas, particularly during the irrigation period, and adequately treating water before discharging it into the rivers. The models provided a helpful tool for conducting a non-point source phosphorous investigation in the Sengari Reservoir to prevent excessive pollution from nutrient load.

In Chapter 5, land-use change scenario testing was applied in the Hatsuka River basin with the aim of quantifying the effect of land cover change on PO_4-P load in the basin. PO_4-P was estimated by water quality predictive model and different non-point source load was quantified. Scenarios under depopulation and land abandonment are tested by converting 10% and 50% of paddy field, and residential area to grass land. Agriculture intensification scenario was tested by converting residential areas to paddy field. Highest non- point source PO_4-P load was from the forest as it occupies the largest portion of land in Hatsuka River basin followed by paddy field and residential areas. Reduction of PO_4-P load was witnessed under the scenario of converting 10% and 50% of paddy field to grass land, and residential area to grass land. With declining farming due to reduced population, it is recommended that abandoned land should not be left bare. Converting them to grass land will reduce significant PO_4-P load in the basin. Management of PO_4-P load in the Hatsuka River basin is subject to decision making on proper utilization and management of abandoned lands, paddy fields, and forest management.

In Chapter 6, SWAT model was applied in the Hazu River basin to simulate discharge and total phosphorus (TP) load. Phosphorus load from different land-use was quantified and effect of Onsite Wastewater Treatment System (OWTS) on TP assessed in the basin. The model was constructed based on the local data which included climatic, hydrological, water quality, spatial soil, elevation and land-use from the relevant authorities. The simulation period ranged from 2009 to 2015. Sequential Uncertainty Fitting Algorithm

(SUFI-2) was used as the optimization tool for model calibration and validation. The model yielded satisfactory performance based on evaluation criteria for both discharge and TP load simulation. Forest areas accounted for the highest load in the basin followed by agricultural and residential areas. When septic tanks are replaced by the sewer system, TP load declines by 0.2% at the basin outlet and 1.5% at the subbasin where majority of septic tanks are located. The model can be significant in quantification and management of non-point source (NPS) phosphorus load flowing into the Sengari Reservoir to help in the preservation of water quality.

7.2 Future prospects

Physical based models require a lot of data to develop. In most regions especially in developing countries it is difficult to find streamflow data, water quality, precipitation and other historical data required for model development. In determining non-point source pollution, water quality predictive model herein developed can be effective in areas with inadequate data to build a physical based distributed watershed model. Future prospects entail application of water quality predictive model in different catchments with diverse land cover and evaluation of its performance. Impact of land cover change on other water quality parameters can also be investigated. In the Sengari Reservoir watershed focuses on phosphorus because of current eutrophication problem in the reservoir.

A more comprehensive land use model can be developed for decision making. Economic and social aspects can be taken into consideration to formulate a more informed land utilization model that minimizes water pollution while maximizing the economic activities that promotes social wellbeing of a particular area.

The model can also be applied in bigger watersheds. Although numerous sampling points and water quality analysis will be labor intensive in a big catchment, it is worth the investment considering the health of the general public and sustainability of the environment is more important.

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