Decision Support Systems for Water Environment Management in Rural Areas under Hydrological and Socio-Economic Uncertainties

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CHAPTER 1 Introduction

1.1 Water Environment Issues in Intensive Agricultural Areas

In the year 2050, the world population would be approximately 9 billion (Tomlinson, 2013). This means an additional 1.7 billion more people to feed than in 2016. In parallel, food consumption per person and demand for higher value secondary diet products, such as meat, dairy products and eggs would continue to rise (Van Hofwegen and Svendsen, 2000). The imperative need to double the global food production by 2050 has therefore become ubiquitous within the international policy arena of food security (Tomlinson, 2013). Annual cereal production would need to rise to three billion tons and annual meat production to 470 million tons (FAO, 2009). Yet, on the other hand, the competition for land and water resources between agricultural and industrial would worsen. Urban and industries would continue to push against the frontiers of arable productive land justified by higher benefit-cost ratios (Tan et al., 2005). About 70 percent of world population would be urban by 2050 (Ahern, 2011). Therefore, in order to feed this larger and more urban population, under conditions of limited land and water resources - more food per unit of land and unit of water has to be produced.

Efforts to achieve this herculean task have been and would continue to be largely through intensive use of land and water resources already under agriculture. The intensive use of agrochemical fertilisers and pesticides, high yielding crop varieties, irrigation, mechanization, and intensive livestock farming systems therefore, characterize many rural areas (Matson et al., 1997). In the intensive agriculture rural areas yields have dramatically increased demonstrated by long-term yield patterns for corn, rice and wheat in both developed and less developed countries (Ray et al., 2012). The intensive agricultural practices, including large agricultural subsidies in the United States, EU and Japan, have both increased food availability and decreased the real costs of agricultural commodities (Tilman et al., 2002). In some regions of sub-Saharan Africa and Asia, crop production is still constrained by too little application of fertilizers (Anderson, 2015). Therefore, intensive high-yield agriculture is highly dependent on addition of fertilizers, especially nitrogen fertilisers (Tallaksen et al., 2015).

However, the resulting intensive agricultural practices have incurred costs related to environmental degradation, loss of biodiversity, loss of ecosystem services, and the long-term stability of agricultural production (Matson et al., 1997). Among other issues, the intensive applications of agro-fertilisers and excessive irrigation withdrawals in the rural areas have attracted the global attention (Tilman et al., 2002). The heavy applications of fertilisers are the major contributor to nutrient loading of receiving waters, including nutrient enrichment that leads to adverse environmental and economical consequences (Matthews et al., 2012). The excessive irrigation withdrawals in intensive agricultural areas have on the other hand drastically reduced the assimilative capacities of water resources (Zhi et al., 2015). Therefore, contamination of groundwater and downstream surface water systems is now frequent in many rural areas (Eneji et al., 2013). Nitrate concentration in the major rivers has increased three to tenfold - an increase directly related to nitrogen fertilization as well as other human activities (Matson et al., 1997). Many of freshwater and marine environment are eutrophicating because of nitrogen (N) and phosphorous (P) lost in runoff or leaching from agricultural systems. There are many incidences of nuisance algae blooms causing hypoxia conditions in freshwater and marine ecosystems leading to loss of aquatic life including fish and shellfish (Smith et al., 1999). High nitrate concentrations also represent a human health concern (Ward, 2009). Other associated complex environment issues include salinization and increased greenhouse gas emissions (Ali et al., 2015). Agriculture affects and is affected by its natural environment. No other sector is more sensitive to the environmental conditions than the agriculture sector. The unsustainable agriculture intensification practices are therefore also indirectly diminishing the finite water resources available for agricultural production by agrochemical pollution and overexploitation.

1.2 Roads to Sustainable Agriculture

In many countries, there are already established efforts to promote a more sustainable means of agricultural production (Luo et al., 2014). In the management of the water environment, the efforts have focused on i) sustainable intensification of agriculture, ii) operating agriculture within the biodiversity and contaminants limits and iii) building resilience to environment water protection in the agricultural and food systems (Soussana, 2014). In that context, integrated fertilizer management approaches have received increased attention as pathways to sustainable high production agriculture and reduction of environment water problems in the rural areas.

Recent concerted efforts recommend applying fertilisers at rates consistent with sustainable yields rather than potential yields (Ali et al., 2015). Others propose use of slow release fertilisers (Oh et al., 2006), use of fertilisers that inhibit nitrification (Morita et al, 2002), and conjunctive use of nitrogen fertilisers with carbonates (Nakasone et al, 2002) and biochar (Eneji et al., 2013). Other efforts include precise spatial and temporal fertiliser applications matched with plant demand (Tilman et al., 2002), and increased use of organic matter to increase the soil capacity to retain the applied nutrients (Steiner et al., 2007).

Various legislations have been instituted to promote sustainable agriculture practices. In 1999 the 'law for promoting the introduction of sustainable agricultural practices' including fertilization was established in Japan (Kumazawa, 2002). Outside the agricultural systems, there are also legislated effluents limitations on total amounts of pollutant loadings for specified water bodies like groundwater, rivers, lakes, and sea. In 1999, the Japanese Environment Agency established the environmental water quality standard on nitrate concentration to be 10 mg/L or less under water pollution control (Kumazawa, 2002). Commenting on the past and current on-field efforts and legislatives, significant reductions of the agrochemical pollutant loadings in the environment waters surrounding the intensive agricultural areas have been observed where the recommended measures have and are being practiced (Hirono et al., 2009).

However, in many such rural areas, the agricultural runoffs and drainage leachates from the agricultural systems are still carrying nutrient loadings enough to pollute surrounding and downstream water bodies (Mabaya et al, 2016c). On the other hand, after many decades of research and development around the topic of fertiliser reduction and efficiency use, there is a growing opinion that further on-field control measures would not achieve major additional benefits on environment water quality without significant cost on agricultural productivity (Luo et al., 2014). For example, further fertiliser reductions than the recommended measures might reduce the quality and yields of agricultural produce (Hirono et al., 2009). In addition, given the interactions of various agroecosystems within river basins, the different goals on maximizing profits and minimizing costs also pose a challenge on how to reconcile different socio-economic activities with the environment (Tilman et al., 2002). Furthermore, in the enforcement of legislation, there has been vagueness on the relevance between water quality standards and limitations. There is some doubtfulness on whether the observance of specified effluent limitations are leading to specified water quality standards (Maeda, 2002).

Moreover, it has also been difficult to control effluents from agriculture given their non-point source character (Kumar, 2003). Beside, the agrochemical pollutant loads dynamics are stochastic in nature. The decreasing or the increasing rate of fertilizing pollutants is affected by temporal and spatial variations of various hydrological variables, and the physical and biological variables of the agricultural system being controlled, whose behaviour is individually stochastic (Billy et al., 2013). More so, while there have been a remarkable improvement in predicting future dynamics of environment water quality constituents, estimation errors and differences between the predicted and the actual ones are still problematic which pose a risk in the management of environment objectives (Cabecinha et al.,2007). Therefore, in reality, achieving sustainable agricultural development still presents one of the greatest scientific challenges because of trade-offs among competing socio-economic and environmental goals, coupled with the stochastic nature of the key hydrological, biogeochemical and ecological processes. On the other hand, as the environmental concerns are increasing, so are the concerns of feeding the growing population (Godfray et al., 2010). Accordingly, an increased world food production with greater protection of the environment for the future presents a major challenge for science (Soussana, 2014).

There is a need to develop more resilient decision support systems in the rural areas, which facilitate greater protection of the water environment from agrochemical pollution and water depletion while sustaining the productivity in the agricultural areas. Such systems should be able to work towards finding innovative sustainable and resilient solutions for the agro-fertilizers nutrient paradox in the rural areas. The aforesaid problems need to be thoroughly identified, options for increased productivity with greater protection of the water environment should be guide posts for action, and incentives must be created and stakeholders must able to participate, while progress is monitored.

1.3 Research Objectives

The overall objective of this research is to develop decision support systems for water environment management of agrochemical pollutant loads from intensive agricultural systems in the rural areas under hydrological and socio-economic uncertainties, using optimization theories. The developed decision support systems would assist to support the decision-making process for improving the surrounding water environment quality and the overall agricultural productivity in the rural areas.

This study is undertaken with the following main objectives:

[1] To develop a robust optimal model for diversion of fertilizing-nutrients polluted agricultural drainage water from an intensive agricultural system to different wetland types under uncertainty using portfolio optimization approach.

[2] To investigate, with an aid of the robust optimal model, the potential of converting fertilizing-nutrients polluted agricultural drainage water into valuable nutrient resources for an alternative cropping system where the nutrients are limiting for crop production.

[3] To develop a reservoir operation model that uses dynamical water quality management approach for stochastic optimal control of agro-fertilizer pollutant loads from intensive agricultural systems into reservoirs for irrigation.

[4] To explore, with an aid of the developed reservoir operation model, how to increase the water environment productivity of the rural areas under constraints of spatial and temporal water shortages and pollution.

1.4 Structure of This Thesis

This thesis consists of six chapters, including this chapter.

In Chapter 2, decision support systems are defined. The established decision support systems for water environment management in the rural areas are discussed. The chapter also describes why optimization-based decision support models are ideal for water environment management focusing in particular on the rural areas.

Chapter 3 describes the robust optimal policy model for diversion of fertiliser nutrient polluted agricultural drainage water from an intensive agricultural system to different wetland types under uncertainty. The chapter details how the intensive agricultural practices in green tea plantations are contributing to the nitrate pollution of surrounding and downstream surface water bodies. Then, the robust optimal model is developed and applied to support decision-making process for diversion of nitrate-contaminated drainage water to different wetland types in order to reduce nitrate loads entering into and polluting the receiving surface waters. The opportunity of converting fertilizer-nutrient polluted agricultural drainage water into valuable nutrient resources for paddy-rice production systems using the model is also investigated.

Chapter 4 presents an optimal operation model for stochastic optimal control of agrochemical pollutant loads from intensive agricultural systems into reservoirs for irrigation. The chapter explores how the reservoirs well posed to intercept substantial fertiliser runoffs from upslope agricultural fields could influence the downstream riverine transport of fertilizer nutrients during operation for irrigation. The model is applied to the study area of interest.

Chapter 5 explores an opportunity to increase environment water productivity in the agricultural areas under problems of agrochemical pollution with an aid of reservoir optimal operation model. The chapter describes how the model could support decision-making process for upgrading to integrated irrigation aquaculture to improve the overall agricultural productivity, under constraints of spatial and temporal water shortages and agrochemical pollution.

In Chapter 6, the conclusions of this study are summarised, and the comments on the future of this research are described.

CHAPTER 2 Literature Review

2.1 Introduction

This chapter defines decision support systems and provides literature reviews on decision support systems for water environment management. The chapter also describes why optimization-based decision support models are ideal for water environment management focusing in particular on the rural areas.

2.2 Decision Support Systems

The first paper that advanced the decision support system (DSS) idea was of Little (1975) where he proposed circumventing the human intermediary by developing an interface for the manager. Since then, the DSS technology and application have evolved significantly to help tackle the semi-structured and unstructured decision problems (Mysiak et al., 2005). However, there has been no established definition of DSS. The ambiguity of DSS definition has been discussed by several authors (e.g. Keen, 1981; Eom and Lee, 1990; Mysiak et al., 2005). As a result, some authors use a very loose definition such as any system that supports decision-making (Mysiak et al., 2005). DSS specifically target, the interface between science and practitioners to provide operation solutions that support decision-makers in dealing with complex problems of the system under study at various scales (Giupponi and Sgobbi, 2013). It appears, therefore, to be the general agreed definition to define DSS as interactive computer-based technology solutions that support decision-making to solve either unstructured or semi-structured or wicked problems (e.g. Eom and Lee, 1990; Shim et al., 2002; Power et al., 2015).

The mode of assistance provided by DSS could also be used as the criterion to differentiate and therefore define specific DSSs. Power et al., (2015) differentiate DSSs as communication-driven DSSs, document-driven DSS, data-driven DSSs, knowledge-driven DSSs and model-driven DSSs. This study specifically deals with the model-driven DSSs. The model-driven DSS usually consists of three major components - model subsystem, data subsystem and user interface (Eom and Lee, 1990). Moreover, they are often categorized into optimization and simulation models (Power, 2002). Therefore, the mathematical and analytic models are the dominant components of such DSSs. A simulation model is a representation of a system used to predict the behaviour of a system under given set of conditions (Wurbs, 1993). As such, alternative executions of simulation models are made to analyze the performance of a system under varying conditions as alternative operating policies. On the other hand, optimization models involve mathematical formulation in which a formal algorithm is used to compute a set of decision-variables values that minimize or maximize an objective function subject to constraints (Ben-Tal et al., 2009).

Although optimization and simulation are two alternative model-drive DSS approaches with different characteristics, their distinction is somewhat obscured by the fact that most models, to various degrees, contain elements of both approaches. While, the core function of each model-driven DSS is to target decision analysis (DA), some usually include capabilities for simulation modeling (SM), and in some cases participatory processes (PP) (Giupponi and Sgobbi, 2013). SM provide a framework for modeling the phenomena of the system, physical or otherwise, and understanding the consequences of decision or of other drivers on the system under-study, thus, making the problem's solution trivial (McCown, 2002). For that reason, simulation models often stand alone as DSSs (McCown, 2002). The PP paradigm embodies tools that enable adequate management of concerns, aspirations and constraints of stakeholders to the decision-making process to provide transparent and end-user satisfaction decisions (Giupponi and Sgobbi, 2013). DA includes the methods, frameworks and algorithms that structure the complex decision problems on different aspects of pursued decisions to provide scientifically sound, technically robust and unbiased judgments (Giupponi and Sgobbi, 2013). DA, SM and PP approaches as DSSs on their own have flaws and shortcomings which may have significant impacts on the final decision, but, a DSS which is able to integrate two or three of these three dimensions, provide operational solutions for the decision process in its entirety (Giupponi and Sgobbi, 2013).

The ultimate goal of a DSS is to improve the performance of decision making by merging human intuition judgment and computer system (Eom and Lee, 1990). Therefore, a successful DSS should be able to explore the problem being dealt with, derive possible solutions, and to discover and analyze the underlying cause-effect relationships (Mysiak et al., 2005). Moreover, a DSS should be simple, robust, easy to control, adaptive, as complete as possible and easy to communicate with (Little, 1975). Nevertheless, the underlying is DSSs support but do not replace the judgments of the individuals, and they improve the effectiveness rather than efficiency of decision process (Janssen, 2012). Therefore, the focus must be on the quality of the decision process rather than quality of final decision.

2.3 Simulation Model-driven DSSs for Water Environment Management

Decision support for planning and management of water environment often consider many target criteria simultaneously like water availability, water quality, flood protection, agriculture and ecology (Haberlandt, 2010). Simulation models, therefore, have attracted much interest in the field of water environment, mainly because of their capabilities to imitate the behaviour or phenomenon of specific water environment physical system. Simulation models are used for both prediction and exploration of the static or dynamic behaviour of the system, plus to anticipate the effects and assess the consequences of simulated phenomena (Power, 2002). When simulation is providing the functionality of the DSS, multiple 'runs' of the experiments are usually executed and the results of each 'run' are recorded and then aggregate results of each test are recorded and then analyzed to try to answer specific questions.

The water environment models used in a simulation can capture much detail about a specific physical system, but how the complex the model should be depends upon the purpose of the simulation. Worldwide, hundreds of hydrological and eco-hydrological models have been developed to simulate processes like infiltration, runoff generation, groundwater recharge, evapotranspiration, nitrate and phosphorous dynamics, erosion, etc (Haberlandt, 2010). The models have also undergone a long period of development from a single factor to multi-factors, from static state models to dynamic models, from deterministic to stochastic, from point source to non-point source, from zero dimensional to one-dimensional, two-dimensional and three-dimensional (Wang et al., 2013).

There are typical commercial simulation models for water environment management, focusing especially on the rural areas. QUAL models were developed from 1970 to 1987 to simulate non-point source pollution particularly in dendritic rivers (Brown and Barnwell, 1987).

WASP1-7 models were developed in 1983 for water quality simulation in rivers, lakes, estuaries, coastal wetlands and reservoirs, including one-, two-, and three dimensional models (Ambrose et al., 1988). Later, Williams et al (1985) developed a Simulator for Water Resources in Rural Basins (SWRRB) model for simulating hydrologic and other related processes in rural basins. The objective was to predict the effect of management decisions on water and sediment yields with reasonable accuracy for ungauged rural basins. The Denmark Hydrology Institute (DHI) developed MIKE models: MIKE 11 (DHI, 1993), MIKE 21 (DHI, 1996a) and MIKE 31 (DHI, 1996b) to simulate flows, sediment transport, eutrophication and other water quality phenomena in estuaries, rivers, irrigation systems and other water bodies in one-, two-, and three dimensional, respectively. QUASAR model was established in 1997 for dissolved oxygen simulation in larger rivers and it is a one-dimensional dynamic model (Whitehead et al., 1997). BASINS models were also established in 1996 as multipurpose analysis environmental analysis systems, suitable for water quality analysis of both point and non-point source pollution at watershed scale (Cao and Zhang, 2006). Arnold et al. (1998) and Arnold and Forer (2005) developed a SWAT (Soil Water Application Tools) model which is a semi-distributed model capable to simulate runoff, nutrients and other agricultural chemicals as well as sediment yield in large complex agricultural watersheds with varying soils, land use, and management conditions. The above-mentioned water environment simulation models have been widely applied worldwide (Wang et al., 2013). There are also other vast models, too numerous to mention, including the empirical and mechanistic deterministic/stochastic models that have been and continue to be developed to simulate complicated water environmental conditions.

Due to special water environment issues like pollution, which can bring serious consequences especially on aquatic and the biodiversity, the water environment effects have to be simulated, predicted and assessed. This make the simulation models important tools for water environmental management decisions. The simulation models provide a framework for modeling the phenomena of the water environment system, physical or otherwise, and also provide the understanding of the consequences of decision or of other drivers on the system under-study, thus, making the problem's solution trivial (McCown, 2002). As a result, the decision-maker can communicate with the simulation model-driven DSS and compare the simulated results to the desired state given by the water environment management objectives. Several measures can be selected to analyze how to achieve the objectives. The capacity of simulation models to give the quantitative insight and current information also enables optimization of control strategies for the strategic or operation decision (Power, 2002).

However, a number of the typical simulation models are complex for non-scientists; need a large number of parameters and data in total, while calibration takes a long time (Haberlandt, 2010). Perhaps, the major setback of the simulated models as DSSs has been the big differences of the simulated results among the models, due to different theories and algorithms used (Wang et al., 2013; Haberlandt, 2010). This often leads to different water environmental management decisions, as most of the modeling results cannot be compared or referred to each other (Wang et al., 2013). The significant uncertainty in the modeling results leaves the serious problem of which model is to be preferred for decision support. Standardization of simulation models can help guarantee consistency in the application of the models for water environment decisions (Wang et al., 2013). Haberlandt (2010) proposes a possibility to improve decision support through integration of the results of the models using fuzzy-set theory or the metamodel approach. Simulation models as DSS are also deficient in that they cannot solve the problem by outputting an optimal action, and often fail to reduce the information to relevant action results leading the users to be overwhelmed with complexity and information (McCown, 2002).

2.4 Optimization Model-driven DSSs for Water Environment Management

The management of water environment in the rural areas sometimes can simply meant monitoring some water quality indices or releasing required irrigation water from the reservoir to the command area (Kawachi et al., 2003). However, water environment management decisions are often complex and multifaceted, principally because of trade-offs between environmental, ecological, socio-political, and economic factors (Kiker et al., 2005). Additionally, the water environmental management problems like any other real world problem are characterised with some data uncertainty. As a result, one cannot ignore even quite small perturbations of uncertain data coefficients as it can make the nominal optimal solutions heavily infeasible and thus practically meaningless (Ben-Tal et al., 2009). This therefore calls for the water environment to be managed from a scientific point of view. While attempts are sometimes made to use intuitive or heuristic approaches to simplify complexities, in the process, important information happens to be lost, while opposing views are discarded and uncertainties are ignored (McDaniels et al., 1999). Developing an optimization model as a decision support tool is quite reasonable because optimization theory has functions to fulfill these requirements.

Optimization methods based on mathematical models are able to define the complex water environmental management problem into a well-defined set of optimization problems. Dividing a complex management problem into several optimization problems and linking the optimization methods for those problems together provide a management strategy as a solution to the original problem (Kawachi et al., 2003). In addition, the linkage of such optimization methods provides a solution to the original problem. Optimization models are formulated in terms of determining values for a set of decision variables that will maximize or minimize an objective function subject to constraints (Wurbs, 1993). An optimization problem in general comprise of the following components: i) control variable constrained in a set of admissible control, ii) a state variable that is given for a chosen control variable as the solution to an equation describing the model of the controlled system, iii) an observation variable of the state variable, and iv) a functional of control variable (Ben-Tal et al., 2009). An optimization model normally incorporates only one objective function, and if there are multiple objectives, they can be combined in a single function if expressed in commensurate units (Wurbs, 1993). Alternatively, other approaches are typically adopted to analyze trade-offs between objectives. One approach is to execute the optimization model with one selected objective function, while the other objectives are treated as constraints at user specified levels (Ben-Tal et al., 2009). Another alternative approach is to treat each objective, as weighted component of the overall objective function (Wurbs, 1993).The optimal problem is to search a control variable that minimizes or maximizes the objective functional. In some cases optimality condition theoretically characterize the optimal control variable, but in some cases, a computer implements an optimization procedure to search the control variable satisfying the optimality condition (Kawachi et al., 2003).

Most optimization applications to water environment management involve linear programming (LP), dynamic programming (DP), and/or search algorithms, and also various other non-linear programming methods (Wurbs, 1993), through the paradigms of robust optimization (RO) and stochastic optimization (SO). The validity of the linear control theory for dynamic problems and that of linear programming for static problems are remarkable in uncertain situations (Kawachi et al., 2003). The uncertain LP problems are associated with deterministic counterparts. LP has advantage over other optimization methods of being a well-defined, easy to understand, and readily available algorithm (Ben-Tal et al., 2009). Therefore, many water environmental management problems can be represented realistically by a linear objective function and set of linear constraints. On the other hand, non-linear properties of a problem can be readily reflected in a DP formulation. Unlike LP, which is a precise algorithm, DP is the general approach to solving optimization problems and is applicable to problems that can be formulated by optimizing multiple-stage decision process (Wurbs, 1993). Search algorithms usually are effective when they are combined with a complex simulation model. The simulation captures the complexities of the real world operation problem, while the search algorithms provides a mechanism to systematize the series of iterative executions of the simulation model required to find a near optimum decision policy (Wurbs, 1993).

The literature related to optimization models in general and application to water environment management in rural areas in particular is extensive. Many researchers have presented several approaches combining mathematical modeling and computational optimization. Kawachi and Maeda (1999) rearranged a finite element and linear programming model and applied it for stream-water pollution control. Kawachi and Maeda (2000) and Maeda et al. (2000) developed robust optimization models to manage water quality in river systems under uncertainty. Kumar et al. (2001) presented a combined method of linear programming and GIS technique to optimize the allocation of discharged pollutant loads from non-point sources in a watershed. Unami and Kawachi (2001) and Unami et al. (2001) incorporated H controllers for an automatic control system for an open channel network and in a decision support system for water quality management in a lake, respectively. Ines et al. (2006) combined the remote sensing-simulation modeling and genetic algorithm optimization to explore water management options in irrigated agriculture. Zhang et al. (2009) developed a robust chance-constrained fuzzy possibilities programming model for water quality management within an agricultural system, where solutions for farming area, manure/fertilizer applications amount, and livestock husbandry size under different scenarios are obtained and interpreted. Belaineh et al. (1999) presented a simulation/optimization model that integrates linear decision rules, detailed simulation of stream/aquifer system flows, conjunctive use of surface and groundwater, and delivery via branching irrigation canals to water users. Huang et al. (2012) developed a stochastic optimization model for supporting agricultural water management and planning in a river basin. Unami et al. (2015) developed a stochastic model to support control of rainwater harvesting system for irrigation during dry spells. There are also other vast optimization models, too numerous to mention, that have been and continue to be developed support decision-making for sustainable water environment management in the rural areas. The review of Singh (2015) gives a detail of various optimization approaches for the management of water environment problems of irrigated agriculture in rural areas.

The advantages of optimization models is that they i) facilitate a more prescriptive analysis, and ii) they provide a more systematic and efficient computational algorithm (Wurbs, 1993). However, representing the objectives, performance character, operation rules, and physical and hydrological of the system in the required format, without unrealistic simplifications are particularly difficult aspect in the application of optimization techniques (Wurbs, 1993). Since water environment problem is often triggered by hydrological phenomena, hydrodynamic simulation models need to be developed before proposing an optimization model (Maeda et al., 2010). As earlier discussed, simulation models have the advantage of providing a more detailed and realistic representation of the complex physical and hydrological characteristic of water environment system. In this regard, simulation models support optimization models by generally providing the mechanisms for the model user to define the operating rules in a greater detail (Wurbs, 1993). Alternatively, utilization of simulation models without any support of optimization models may lead to inefficient and/or subjective decision making (Maeda et al., 2010). For example, while to some extent, simulations of water flows and pollutant transport can provide management alternatives in the decision-making process, however, screening these alternatives remains a difficult problem because numerous options can be created. Therefore considering many existent physical and socio-economical conditions, an optimization approach for selecting a promising management alternative would be required. Therefore, simulation and optimization models should not be rigidly categorized as being descriptive and prescriptive, respectively (Wurbs, 1993).

The review shows that there is no single type of water environment problem but, rather, a multitude of decision problems and situations. Each water environment system and each study is unique, therefore, a variety of decision variables, decision criteria, and constraints can be incorporated using either simulation models or optimization models or integrated simulation-optimization models. In this study, a complex water environment management problem under hydrological and socio-economic uncertainties in the rural area under study was divided into several optimization problems and the optimization methods for those problems were linked together to provide the solution to the original problem. Optimization models and simulation-optimization models are used as decision support systems.

CHAPTER 3 Robust Optimal Model for Diversion of Agricultural Drainage Water from Intensive Agricultural Systems to Paddy Fields

3.1 Introduction

Green tea is a very profitable crop that thrives on a robust domestic consumer market, where often the price thereof reflects the quality of tea (Gweänaelle et al., 2004). The major quality indicator of green tea is the content of free amino acids (Ruan et al., 1998). The amino acids give the sweetness often used to describe high quality green teas (Gweänaelle et al., 2004). Accordingly, the most important nutrient in green tea production is nitrogen (N). In pursuit of high quality tea, it has been the general tendency by green tea farmers to apply heavy dressing of N fertilisers. N application rates of 1,000-2,500 kg N $ha^{-1}year^{-1}$ are reported to have been applied to green tea crop (Hirono et al., 2009; Ii et al., 1997; Nagumo et al., 2012; Oh et al., 2006). Thus, N fertiliser applications in green tea plantations have been much higher than any other field crop land use. Consequently, this intensive use of N fertilisers has made green tea plantations one of the highest N-pollutant emitters to water bodies among land use categories in Japanese agricultural watersheds.

When N is applied to soil, it undergoes various transformations and movements within the crop and soil systems. Nitrate-nitrogen (NO_3-N) is the common transformation often undergone by N in the soil system. NO_3-N is very mobile, and is easily lost from soil system through leaching and runoff to water bodies, and its concentration tends to vary seasonally and spatially in an agricultural watershed (Hirono et al., 2009; Poudel et al., 2013). The N fertiliser applied in winter and spring, which becomes nitrified, tends to remain in the surface soil of tea plantations until the rainy season when it is later leached away to water resources. As a result, the NO_3-N concentration in tea plantations tends to be highest in winter and lowest in summer season (Hirono et al., 2009). The fluctuation is opposite to drainages, surface and subsurface waters around green tea plantations where NO_3-N concentration tends to be highest during the summer season (Hirono et al., 2009; Ii et al., 1997). This phenomenon occurs more often when no buffer is present in the lower reaches of the watershed (Vidon et al., 2008).

In Japan, severe NO_3-N contamination of water resources is increasingly being observed in intensive green tea growing regions than in any other cropping regions. High NO_3-N concentration of water resources is a greatest environment threat to public and biodiversity. Most water sources such as springs and deep wells originating from nearby tea plantations are reportedly no longer safe for drinking due to high NO_3-N concentrations (Ii et al., 1997). Excess levels of NO_3-N concentrations in drinking water are linked to diseases like methemoglobinemia and gastric intestinal cancer (Comly, 1987). Apart from eutrophication of water resources, excess NO_3-N in running and standing waters has also been the main cause of aquatic life extinction in tea dominated watersheds due to the decrease in dissolved silica and pH (Nagumo et al., 2012; Nakasone et al., 2002). A typical example is the study by Nakasone et al. (2002) where they reported the total absence of aquatic life in Tanno Reservoir in Shizouka Prefecture, Japan, due to strong acidity caused by nitrate inflows from nearby tea plantations.

A number of (predominantly fertiliser related) countermeasures are recommended to farmers in Japan to solve the problems of nitrate contamination of waters in tea dominated watersheds. These include reducing chemical N fertilisers use to optimal application rate of 540 kg N ha^{-1} $year^{-1}$ (Nagumo et al., 2012), use of high N efficient fertilisers (Oh et al., 2006; Ii et al., 1997), conjunctive use of carbonates with N fertilisers (Nakasone et al., 2002), and use of organic green manure (Kumazawa, 2002). A follow-up study by Hirono et al. (2009) after 10 years of implementation of these measures in Makinohara tea area in Shizuoka Prefecture, Japan, showed a significant NO_3-N reduction in water bodies surrounding tea plantations. However, despite the decreasing trend, the annual average NO_3-N of water resources from tea growing regions remained above 10 mg/L (Japan environment water quality threshold). This phenomenon was also noted in our study area in Shiga Prefecture, Japan, where measured seepage and runoff flows from cliffs in the forests surrounding the tea plantations flowing directly into adjacent river recorded high NO_3-N contaminations throughout the year (Mabaya et al., 2014a). Hence, the current recommended maximum fertiliser application rates for tea crop could be possibly still high for sound water environment. Unfortunately further reductions in N fertiliser application rates to tea crop might lead to decline in quantity and quality of tea produced (Hirono et al., 2009; Nakasone et al., 2002).

On the contrary, the value of paddy fields located on the valley bottoms of upland tea plantations, goes beyond provision of staple food. Paddy fields and their associated irrigation systems possess abundant multifunctionality roles, which include flood mitigation, ground water recharging, soil erosion prevention, water purification and biodiversity conservation (Huang et al. 2006; Kim et al. 2006; Matsuno et al. 2006; Unami and Kawachi, 2005). However, despite this unique characteristic of multifunctionality, the paddy fields are facing crisis of collapsing (Matsuno et al, 2006). Paddy rice production sector cannot endure without subsidies due to associated high production costs but low market prices (Katayama et al., 2015). The profit inefficiencies of rice production are also due to excess rice inventory worldwide and problems of aging farming community (Matsuno et al., 2006). Paddy cultivation is therefore under threat of abandonment. The threat of abandonment of paddy cultivation in Japan poses as a risk to current environmental sustainability of agricultural watersheds where rice paddy cultivation dominates (Mabaya et al., 2014b). Unfortunately, once paddy field is abandoned, restoration takes long time and it may not even be possible to reactivate all the multi-functions. There is therefore an immediate need to identify the space, degree and beneficiary of the previously mentioned functions of paddy fields to create a partner relationship with other agricultural sectors to generate mutual benefits (Mabaya et al., 2016a).

Paddy rice and green tea crops pose a potential partnership that can generate greatest benefits in both sectors, in terms of profitability and environment sustainability. N is the most limiting nutrient for rice production (Ishii et al., 2011). Therefore, N concentrated drainage water from tea plantations if diverted to paddy fields has potential direct benefit to contributing towards viable production of rice through freely availing most important inputs for rice production, that is, N nutrients and water(Mabaya et al., 2014b). The review paper of Ishii et al. (2011) on N cycling in rice paddy environments showed that, N-transforming processes in paddy fields can effectively reduce N-loads in water and soil through nitrification-denitrification (Hayatsu et al., 2008), plant-N-uptake (Sasakawa and Yamamoto, 1978), and anaerobic ammonium oxidation (Zhu et al., 2011). Moreover, the N-load reduction activity in the paddy is widely reported to show tendency of increase with increase in N concentration in the inflow (Matsuno et al., 2006). Therefore, if N-concentrated drainage water were diverted from tea plantations to paddy fields, paddy fields could potentially act as a constructed wetland, thus purifying water (Matsuno et al., 2006). It is a common phenomenon in Japanese well-drained agricultural watersheds to find either one or both of these two crops dominating (Mabaya et al., 2016a). The topo-sequence nature which tends to be common when both crops are dominating the watershed makes this strategy technically feasible.

However, there are also inherent uncertainties in paddy N-reduction function, due to complex mechanisms in N transforming processes. In the absence of hydraulic control system during the diversion of N contaminated drainage water to lowland paddy fields; there is a possibility of further environment risks like NO_3^- leaching, and production and emission of greenhouse N_2O and health hazard NH_3 gases (Mabaya et al., 2014a). According to Keeney and Sahrawat (1986), these three possible risks are auspiciously very insignificant processes due to strong nitrification-denitrification in paddy soils. Even supposing that, the ratios of NO_3-N, NH_4-N, and NO_2-N reduced to N_2 or up taken by plant are not distinct. Therefore, if N load reduction ratios are not known in advance and problem of inherent uncertainties are not dealt with before diversion of agricultural drainage water to paddy fields; further environment risks cannot be completely ruled out. The effectiveness of diverting nitrate contaminated agricultural drainage water from upland tea plantations to paddy fields in the valley bottoms is investigated in this Chapter. A robust optimal model, which robustly allocates optimal fractions of agricultural drainage discharges from tea plantations for diversion to paddy fields, was developed. The application of the model to the study area of interest, as a decision support system, in terms of its ability to reduce pollution to water resource, to maximize plant N uptake and to minimize further environment risks in the respective paddy fields was analyzed.

In this chapter, section 3.2 discusses how paddy fields can purify nitrate contaminated agricultural drainage water under uncertainty. In section 3.3, a robust optimal diversion model for diversion of agricultural drainage water from intensive agricultural system to paddy fields is formulated. Section 3.4 contains materials and methods illustrating how the robust optimal diversion model could be applied to reduce the nitrate pollution from green tea plantations to the surrounding and downstream water resources, to maximize plant N uptake, as well as to minimize further environment risks in the respective paddy fields In section 3.5, the results of the study are stated and discussed. In the last section, conclusions of the study are given.

3.2 Paddy Nitrogen Reduction Function

The review paper of Ishii et al. (2011) on N cycling in rice paddy environments showed that, there are various possible N-transforming processes likely to occur when N contaminated water from upland tea plantations is diverted to lowland paddy fields. **Figure 3-1** shows the schematic overview of how N-contaminated drainage water diverted could be N-cycled in paddy soils.

Nitrification is a microbial process where NH_4^+ is oxidised to NO_3^- via NO_2^- by nitrifying bacteria (Hayatsu et al., 2008). On the other hand, denitrification is the microbial respiratory process in which N-oxides (NO_3^-, NO_2^-) are stepwise reduced to gaseous forms (NO, N_2O, N_2) by denitrifying bacteria (Ishii et al., 2011). Nitrification-denitrification is the dominant process involved in N-reduction in rice paddy soils (Ishii et al., 2011). Either N_2 or N_2O gas can be the end products of nitrification-denitrification. Due to strong denitrification activity, emission of N_2O gas is usually very low, but N_2 is the major end product of denitrification (Ishii et al., 2011). Denitrification rate of paddy fields is reported to be between 0.02 and 0.8 g/m^2 per day (Matsuno et al., 2006). The nitrification bacteria activity tends to increase with ammonia-fertilization (Freitag et al., 2005). On the other hand, Scheid et al. (2004) revealed an increase of denitrifying activity whenever nitrate fertilisers were added to paddy soils. Therefore diverting drainage water with high NO_3-N and NH_4-N concentrations might speed up nitrification-denitrification process. Nitrification-denitrification rate tends to increase with increase in ponding condition, temperature, organic carbon supply, N concentration of inflow, N fertiliser application and pH (Ishii et al., 2011; Matsuno et al., 2006). Thus, more nitrification-denitrification is expected in summer season, when weather, water management, and agronomic aspects conducive for growing rice crop indirectly create also a favourable environment for nitrification-denitrification process.

Rice plants uptake N in NH_4^+ and NO_3^- forms, where in the presence of both, the crop uptakes NH_4^+ faster than NO_3^- (Sasakawa and Yamamoto, 1978). However, there is growing evidence that partial NO_3^- nutrition further improves the growth of rice. The study by Duan et al. (2007) showed a yield increase of 40-70% where mixtures of NH_4^+ and NO_3^- were used as compared with either forms applied alone. N uptake by rice plants also increases with temperature (Sasakawa and Yamamoto, 1978) and pH (Wang et al., 1993). Additional N fertiliser application by farmers further increases the plant uptake of NH_4^+ and NO_3^- (Duan et al., 2007). Therefore, when the N-concentrated drainage water is diverted to paddy fields, the rice crop might easily absorb NO_3^- and NH_4^+ in their present states for its immediate benefit and in the process purifying water from N contaminant loads. The process is however seasonal, since rice crop can only be grown in summer season in most parts of Japan. Moreover, nitrification-denitrification process being the dominant process in paddy fields means a significant amount of N_2 is lost to atmosphere which should be supposedly used by rice crop.

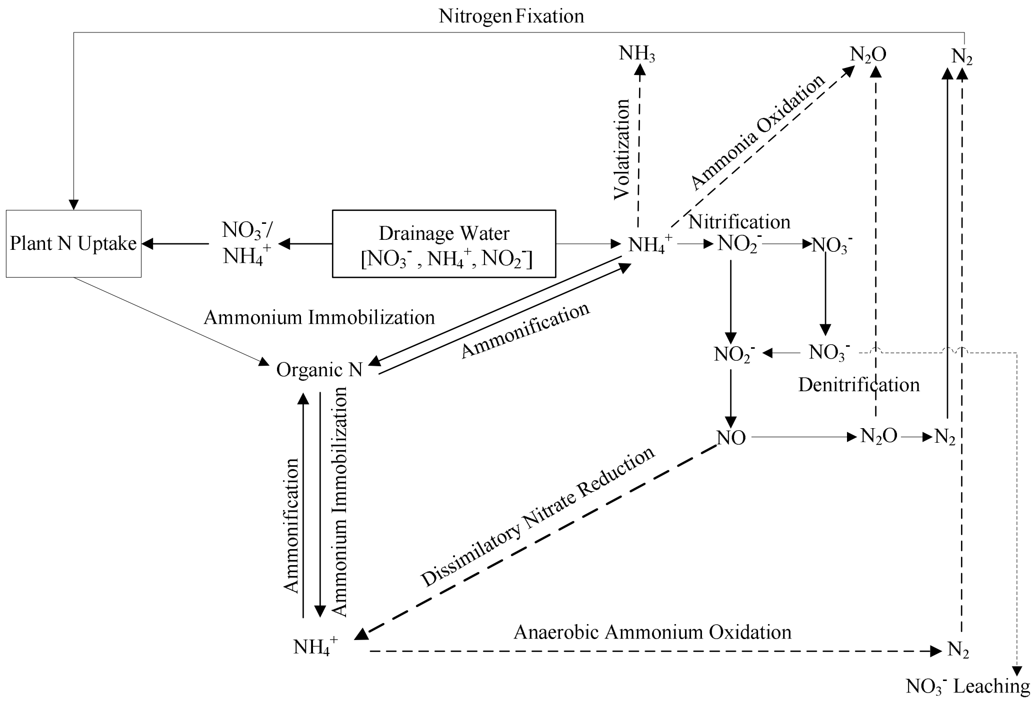

Figure 3-1 Schematic overview of nitrogen cycling in rice paddy wetland soils. The solid and dashed arrows indicate the reactions normally and rarely observed respectively, in paddy fields.

The study by Van de Graaf et al. (1995) reveals that NH_4^+ can also be biologically transformed by anaerobic oxidation to N_2 by *Planctomycets spp.* This process is called anaerobic ammonium oxidation (annamox). Recent study in China show that the annamox activity occurs in rice paddy soils when both NH_4^+ and NO_3^- are both present. Zhu et al. (2011) detected annamox activity in paddy fields of China where both ammonia fertilisers and nitrate concentrated pig manure slurry were used. Therefore, basing on this finding similar to our proposal, diverting water with significant concentrations of both NH_4^+ and NO_3^- could additionally induce an annamox activity; thereby speeding up removal of N contaminants in drainage water. However, annamox activity's detailed contribution to N cycling in rice paddy soils still requires further study (Mabaya et al., 2014a).

N_2O and NH_3 gas productions, and NO_3^- leaching are possible environment risks that may be undergone by N contaminated water if it is deliberately diverted to lowland paddy fields. NH_3 gas is produced and lost to atmosphere when NH_4-N volatises. NH_3 gas is one of the major air and water quality concerns, as it is known to cause significant health hazardous effects to public and environment ecology. The process tends to increase with increase in NH_4-N, soil pH, temperature, wind speed and solar radiation (Keeney and Sahrawat, 1986). Nitrate leaching is another abiotic process where NO_3^- is lost to ground and surface water. It is more prevalent in paddy fields when soils are negatively charged (due to presence of high clay content), which sequently leads to selective adsorption of positively charged NH_4^+ leaving out negatively charged NO_3^- to leaching (Ishii et al., 2011). Nitrate leaching tends also to be high during the draining periods of paddy fields, and after heavy rainfall events especially if soils are of high permeability. Green house N_2O gas can also be produced when NH_4^+ is oxidised under aerobic conditions (Ishii et al., 2011). During denitrification process N_2O can also become an end product when denitrifying bacteria lack N_2O reducing ability (Keeney and Sahrawat, 1986). There are also several other sources of N_2O gas. Therefore identifying sources of N_2O is important in order to establish N_2O mitigating strategies. N_2O gas emission is however, dominant in upland fields where O_2 is not a limiting factor than in paddy fields. Overall, according to Keeney and Sahrawat (1986), these three possible risks are auspiciously very insignificant processes due to strong nitrification-denitrification in paddy soils. However, the ratios of NO_3-N, NH_4-N, and NO_2-N reduced to N_2 or up taken by plant are neither distinct nor known in advance; therefore uncertainties due to implementation errors when agricultural drainage water is diverted to paddy fields cannot be completely ruled out (Mabaya et al., 2014a).

3.3 Robust Optimal Diversion Model

A conceptual framework for the diversion of agricultural drainage water from green tea plantations to paddy fields is presented as in **Figure 3-2**. Let the current agricultural drainage flow dynamics of a given agricultural watershed have a unit discharge with initial NO_3-N concentration C coming from upland tea plantations flowing directly into the adjacent river (R) via the drainage canal (DC). To reduce the NO_3-N entering into and polluting the adjacent river R, a fraction of the unit discharge is diverted from DC to the abandoned paddy fields (APs) and active paddy fields (PFs). The goal is to find the optimal fractions of the unit discharge for diversion, which maximizes the reduction of the NO_3-N entering the R, increases N nutrients accessibility by rice plants and minimizes further possible environment risks like NO_3-N leaching and greenhouse N_2O gas production in the respective paddy fields (Mabaya et al., 2016c). A robust optimization solution is proposed to formulate the above-mentioned problem.

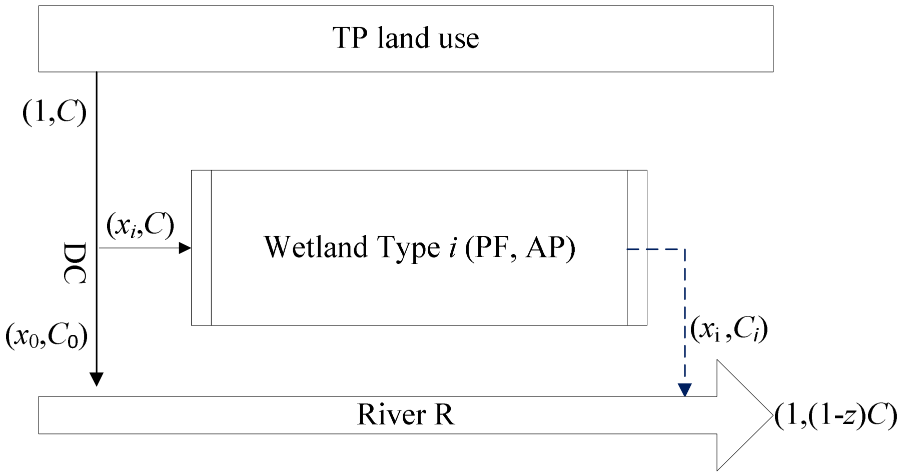

Figure 3-2 Schematic conceptual framework for diversion of unit discharge of agricultural drainage water with NO_3-N concentration C from TPs to PFs, APs and DC, and the resultant discharge amount and NO_3-N concentration to the R. The first element in parentheses represent discharge amount and the second element represents the discharge's NO_3-N concentration. Solid arrows shows direct inflow direction, dashed arrow show the flow direction which could be either impounded or released to R.

Let x_i be the ratio of the unit discharge diverted to the ith wetland type of paddy fields from the DC wetland type, which is assigned $i = 0$ is (that is, no diversion). The ratios x_i are subject to the constraints $\sum_{i=0}^{i<n} x_i = 1$ and $x_i \geq 0$, where n is the number of wetland types. Let p_i be the ratio of NO_3-N reduced in the i th wetland type, defined as

$$p_i = \frac{C - C_i}{C} \tag{1}$$

where C_i is the final NO_3-N concentration of diverted agricultural drainage water in the i th wetland type. When p_i values are distinct and known in advance, the linear programming (LP) problem with the performance index

$$\max\left\{z : z = \sum_{i=0}^{i<n} p_i x_i, \sum_{i=0}^{i<n} x_i = 1, x_i \geq 0\right\} \tag{2}$$

has the optimal solution to divert all the drainage water in the most denitrifying wetland. It is however, difficult to ascertain p_i values in real problems due to inherent uncertainties of complex mechanisms in NO_3-N reduction processes. The uncertainty involved in the N dynamics is assumed to be represented in the constraining ellipsoidal set

$$U^{\theta} = \left\{\mathbf{p} = [p_i] \in \mathbb{R}^n \left| \sum_{i=0}^{i<n} \frac{\left(p_i - p_i^*\right)^2}{\sigma_i^2} \leq \theta^2 \right.\right\} \tag{3}$$

where p_i^* is the nominal value of p_i, σ_i is the radius determining uncertainty interval of p_i, and $\theta > 0$ is the safety parameter chosen by decision maker to reflect his/her attitude towards the possible environment risks from prediction and implementation errors. The larger the value of θ the more risk averse is the decision maker (Ben-Tal and Nemirovski, 1999). The performance index here is redefined as the worst-case NO_3-N reduction

$$z = \left\{\min \sum_{i=0}^{i<n} p_i x_i\right\} \tag{4}$$

Due to the conical nature of the constraint (3), the problem (2) reduces to a feasible nonlinear optimization problem

$$y = \max\left\{z = \sum_{i=0}^{i<n} p_i^* x_i - \theta\sqrt{\sum_{i=0}^{i<n} \sigma_i^2 x_i^2} : \sum_{i=0}^{i<n} x_i = 1, x_i \geq 0\right\} \tag{5}$$

Problem (5) gives therefore the robust optimal policy for diversion of agricultural drainage water from tea plantations to paddy fields and DC. Here, it can be observed that the above policy is a global robust optimization problem in the sense that the robustness constraint of (5) represents all the possible values of p_i. The necessary condition to be satisfied by x_i can be obtained through subjecting (5) to the local extremum condition

$$\left(p_i^* - p_{i+1}^*\right)^2 \sum_{k=0}^{n-1} \sigma_k^2 x_k^2 - \theta^2 \left(\sigma_i^2 x_i - \sigma_{i+1}^2 x_{i+1}\right) = 0 \tag{6}$$

for $0 \le i < n-1$ and the constraint $\sum_{i=0}^{i<n} x_i = 1$.

3.4 Materials and Methods

3.4.1 Description of Study Area

The robust optimal model is applied for diversion of agricultural drainage water from tea plantations to paddy fields for both rice growing season (RS) and non-rice growing season (NRS) in a study area, which is called Imago area, extending over the Nunobiki hills and adjacent valleys of Shiga Prefecture, Japan. **Figure 3-3** shows the map of the study area and water quality sampling points where water quality measurements were conducted.

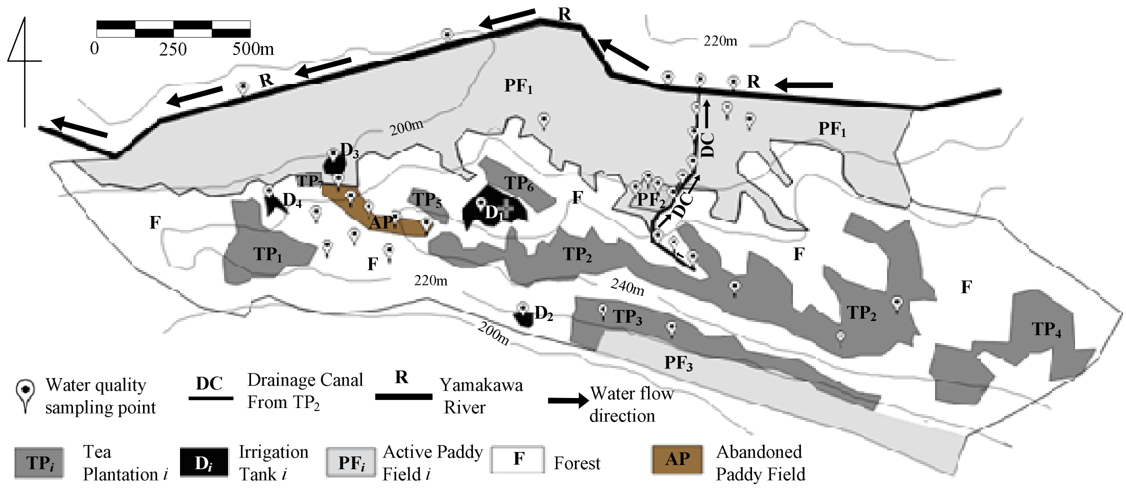

Figure 3-3 Land use configuration of Imago area agricultural watershed and locations of water quality testing points.

The study area has typical land use configuration including rainfed tea plantations (TPs) on hilltops and upper slopes, forests (Fs) on hill slopes, abandoned paddies (APs, i = 1) on upper valley bottoms, active paddy fields (PFs, i = 2) equipped with irrigation and drainage facilities in middle valley bottoms, and irrigation ponds or dams (Ds). The abandoned paddy fields used to be rainfed but were later abandoned after the construction of Imago Dam (D_1) in 1964 to irrigate the middle valley because the upper valley was prone to low water temperatures, lack of sunlight, and crop damage by nuisance wild animals. The total areas of the Fs, APs, PFs, and TPs are 115 ha, 0.6 ha, 57.5 ha and 35.3 ha respectively. Yamakawa River (R), which flows across the valley bottoms, also happens to be the main drainage channel of the study area. Seepage from upland tea plantations and forests seeps out throughout the year mostly from the gorges and cliffs wetting the abandoned paddy fields on upper valley bottom. Some of the seepage and runoff from TPs finds its way into drainage canals (DCs) in the middle valley bottoms, flowing into R.

3.4.2 Green Tea Fertilizer Applications

Table 3-1 shows the fertiliser application methods and strategies that are currently being applied in the green tea plantations (TPs) of the Imago area. The fertiliser application strategies observed include split N application method, use of organic fertilisers, use of high N efficient fertilisers; conjunctive use of carbonates with N fertilisers. The annual N application rate in TPs is about 600 kg/ha; slightly higher than the recommended 540 kg/ha (Nagumo et al., 2012).

Table 3-1 Observed fertiliser types and application rates in TPs of Imago area.

Date of application	Description of fertiliser used	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)
10/02/2014	Organic fertiliser (bone meal, fish meal), ammonium sulphate, potassium sulphate	98	42	56
12/03/2014	Organic fertiliser (bone meal, fish meal) , Controlled release fertiliser (sulfur coated urea)	200	40	56
10/04/2014	Controlled release fertiliser (sulfur coated urea)	146	0	0
10/04/2014	Slow release fertiliser (ammonium sulphate mixed with nitrification inhibitor), carbonates (dicyandiamide)	73	0	0
10/09/2014	Organic fertiliser (bone meal, oil cake), ammonium sulphate, urea	85	16	34
Total annual applications		602	98	146

3.4.3 Water Quality Characteristics Measurements

A 7 × 3 × 4 × 2 × 4 factorial experiment design layout with 7 land use types, 3 water quality measurement items, at least 4 samples measured per land use per water quality item per respective test day, 2 measurements done per month for 4 successive months per each season was used for water quality characteristics measurements. Water quality items NO_3-N, NO_2-N, and NH_4-N were measured using simplified on-site water quality pack tests (Kyoritsu Chemical Check Lab Corp, Tokyo, Japan) on Fs, a DC, TPs, APs, PFs, Ds, and the R, at place marks indicated in **Figure 3-3**. The water quality characteristics were measured from November 2013 to August 2014 twice per month. The observed water quality measurements were divided into two groups: the NRS (from November 2013 to February 2014) and the RS (from May 2014 to August 2014). The averages and standard deviations for each water quality item measured per land use per season were subsequently computed and analyzed by comparing the results among the land use types in a particular season and in between two seasons.

3.4.4 Temporal and Spatial NO_3-N Reduction Measurements in Wetlands

The measurements of temporal and spatial changes of NO_3-N in wetland types were concurrently conducted from November 2013 to August 2014. A 3 ×1× 4 × 2 × 4 factorial experiment design layout with 3 wetland types (of AP, PF and DC), only 1 NO_3-N water quality item measured, (at least) 4 sample points measurements down the slope per wetland type, and 2 tests measurement done per month for 4 successive months per each season was used. The sampling frequency was twice per month; after-no-rain-day (Test 1) and after-rain-day (Test 2). The time span between Test 1 and Test 2 was approximately one week. Test 1 represented equilibrium state scenario and Test 2 represented disturbance scenario. The NO_3-N concentrations of each wetland type under the study on each test day was measured from upstream to downstream for DC wetland type, from inlet to outlet for PFs, and down the slope for APs. The percentage differences of spatial measurements of NO_3-N concentration for each respective wetland type on each respective test day were calculated using Equation (1). Observed NO_3-N changes of the two tests were grouped into two clusters: the NRS and the RS. Temporal and spatial NO_3-N reductions of wetlands were analyzed by comparing the two tests results on the respective wetland type and among the wetland types in a particular and in between two seasons.

3.4.5 Statistical Analysis

The significance of differences of water quality characteristics among land-uses, and temporal and spatial reductions of NO_3-N in wetlands, in a particular season and in between two seasons were statistically compared using Mann-Whitney U one tailed test at 5% significance level. Mann-Whitney U test is a non-parametric test of the null hypothesis that the two populations are the same against an alternative hypothesis that a particular population has larger values than the other. In the results and discussion section, the cumulative distribution function (CDF) value p corresponding to the Mann-Whitney U statistics is calculated for each comparison and mentioned in parentheses.

3.4.6 Operation of Robust Optimal Diversion Model

3.4.6.1 Estimation of the Model Parameters

In the study area, DCs conveyed seepages and runoffs from TPs to the R via APs in the upper valley bottom and PFs in the middle valley bottoms. To operate the robust optimal diversion model in the study area, the three wetland types were considered: DC $(i = 0)$, AP $(i = 1)$ and PF $(i = 2)$. To find the robust optimal allocations of drainage water for the three wetland types; observed NO_3-N reductions during the NRS and the RS in AP, PF and DC wetland types were first calculated. Test 1 measurements (described in section **3.4.4**) were exclusively used per each wetland type as they were more representative of the NO_3-N dynamics in the study area because they were not affected by short-time disturbances of incidental rainfalls.

Depending on which of the observed spatial sampling points confirmed positive NO_3-N concentrations on each respective test day, each wetland type under the study was divided into finite number of reaches. The DC was segmented into reaches from upstream to downstream, while PF was from inlet to outlet, and AP was down the slope. The calculations were conducted specifically on DC that carried seepages and runoffs from TPs to the R via PFs in the middle valley bottoms, and the PF_2 in **Figure 3-3,** which was receiving direct 5 mg/L and 10 mg/L NO_3-N contaminated direct inflow through DC during the NRS and through flume during the RS respectively. The AP investigated was the same wetland where other water quality tests described above were conducted. Observed NO_3-N reductions within each respective reach of respective wetland type were then calculated by applying Equation (1). p_i^* (which is the nominal value of p_i) was taken to be the arithmetic average and σ_i (which is the radius of uncertainty) was taken to be the standard deviation of the observed spatial NO_3-N reductions (%) in the reaches of each wetland type (AP, PF and DC), respectively.

3.4.6.2 Deduction of Robust Optimal Diversions

Applying the Newton-Raphson method to Equation (6) for $0 \le i < n-1$ and the constraint $\sum_{i=0}^{i<n} x_i = 1$, the robust optimal diversions were numerically solved by allocating different rates of diversion x_i to APs, PFs and DC in each season under different safety levels of $\theta > 0$. The resultant performance indexes, which are the total worst-case NO_3-N reductions were then calculated as in Equation (4). The expected risks, which are the worst-case NO_3-N reduction deviations in the NRS and the RS respectively, were calculated as $\sqrt{\sum_{i=0}^{n-1} \sigma_i^2 x_i^2}$. The last stage of robust policy model operation was the selection of best robust safety factor θ for diversion of agricultural drainage water to APs, PFs and DC, which results in best trade-off between large NO_3-N reductions and small NO_3-N reduction deviation. The corresponding robust diversions x_i to APs, PFs and DC of the selected best robust safety factor θ, were accordingly taken to be robust optimal diversions of agricultural drainage water from tea plantations during the NRS and the RS.

3.5 Results and Discussion

3.5.1 Water Quality Characteristics of Land-uses

Figures 3-4 and **3-5** show results of water quality characteristics, observed per land use during NRS and RS, respectively. NO_2-N was absent in all the land use types and in both seasons. The results are expected since, often, NO_2^- is an intermediate (not end) and unstable oxidation state of nitrification process. Otherwise, high levels of nitrite would have indicated a problem of nitrification cycle. On the other hand, small NH_4-N concentrations between 0.2-0.4 mg/L were observed and showed no significant difference ($p = 0.115$) between seasons and respective land use types. This might be a common phenomenon among Japanese agricultural watersheds as it was also observed in the agricultural watershed of Gunma Prefecture, Japan (Ohrui and Mitchel, 1998). The small and unchanging states of NH_4-N among land use types and throughout the year seem to indicate its equilibrium state with the environment.

In contrast, significant and different concentrations of NO_3-N between 0-10 mg/L were observed among different land use types and in between seasons. As expected, forests (Fs) land use type had lowest mean NO_3-N concentrations of 0.1mg/L both in NRS and RS respectively, and showed no significant change $(p = 0.326)$ in between seasons. The observed result is comparable to other previous studies of forest-dominated sub-catchments (Billy et al., 2013; Huang et al., 2012). Irrigation dams (Ds) recorded low mean NO_3-N levels of 0.2 and 0.3 mg/L in the RS and the NRS respectively. The water quality of farm dams showed that it was controlled by hydrology and land use. According to Brainwood et al. (2004) direct precipitation generally comprise less than one tenth of total water input, while surface waters as runoff can comprise nearly all the water in the farm dam. Likewise, low nitrates levels which were recorded in Ds could be due to low nitrate concentration recorded from adjacent F and PF land use type that provided runoff catchment to observed Ds (in **Figure 3-3**). A further investigation of nitrate concentration variation including Ds with TP catchments might also be necessary, especially to understand rate of inventory nitrate over time.

A distinct observation noted was high mean NO_3-N concentration in TPs and DC land use types in both seasons. DC carried seepages and runoffs from TPs to the R via PFs in the middle valley bottoms. TPs recorded mean NO_3-N concentration of 6.6 and 6.4 mg/L in the RS and the NRS, respectively, showing no change $(p = 0.711)$ in between seasons. In contrast, DC recorded mean NO_3-N concentration of 4.0 and 8.3 mg/L in the RS and the NRS, respectively, showing a significant decrease $(p = 0.007)$ during the RS. Tea is a perennial crop, accordingly, high and unvarying NO_3-N concentration of TPs in both seasons can be attributed to frequent application of high amounts of N fertilisers to tea crop in all seasons throughout the year. On the other hand, observed NO_3-N reductions in DC were quite the opposite of most agricultural drainages where NO_3-N concentration tends to be high during the summer season (Ii et al. 1997; Hirono et al. 2009). The reason was due to significant dilution by high volumes of denitrified waters from draining PFs in the middle valley, which drained into DC just before DC discharges into the R. In this regard, deliberate designing of DCs from TPs to pass through PFs (or linking DCs of TPs to DCs of PFs), would result in significant decrease in NO_3-N concentration flows from TPs due to dilution effect especially during the RS.

APs in the upper valley bottoms, just below upland TPs, recorded small mean NO_3-N amounts of 0.1 and 0.2 mg/L in the RS and the NRS, respectively, indicating no significant NO_3-N changes $(p = 0.433)$ in between two seasons. A study by Kogi et al. (2010) in Inba watershed, Chiba Prefecture, Japan where abandoned paddy fields were receiving wastewater from adjacent urban area showed that APs reduced 58% of total nitrogen (T-N) in individual watersheds and 73% of T-N when watersheds were utilized in a consecutive series. Similarly, given that upland TPs formed part of APs seepage and runoff catchment, it appears the APs were also effectively denitrifying high NO_3-N contaminated seepages from just upland tea plantations. This shows that, APs can play an important role in reducing nitrogen pollutant loads especially in agricultural watersheds where both TPs and APs are prevalent.

The PFs in the middle valley recorded mean NO_3-N concentration of 0.4 and 1.2 mg/L during the NRS and the RS, respectively. The increase in mean NO_3-N concentration during the RS was likely due to N fertiliser application activity to rice crop by farmers (Mabaya et al., 2016a). The increase was however, not significant $(p = 0.326)$ despite N fertiliser applications. The observed results in the NRS also showed that APs and PFs had no significant difference $(p = 0.164)$ in NO_3-N concentrations. On the contrary, during the RS, observed NO_3-N concentrations in APs and PFs showed significant difference $(p = 0.026)$ .The results show that NO_3-N loads in APs and PFs are closely linked to seasonal variability scale of hydrological and biogeochemical processes. During the NRS the hydrological and biogeochemical processes both in APs and PFs are likely to be similar (Mabaya et al, 2016c). However, during the RS the agronomical and biogeochemical changes in PFs like N fertiliser application and increased uptake of uptakes of NH_4^+ faster than NO_3^- may explain the NO_3-N increase in PFs (Sasakawa and Yamamoto, 1978). On the other hand, despite the commonality of N fertiliser application activity in both TPs and PFs land use categories during the RS, PFs recorded significantly smaller NO_3-N concentration $(p = 0.002)$ than TPs. Moreover, in the NRS, most PFs recorded nil amounts of NO_3-N in water from N fertiliser residues despite the fact that it was just after the end of the RS. This all may point to effective NO_3-N reduction processes of PFs as earlier reviewed.

The adjacent river (R) which flows across the valley bottoms of the study area recorded mean NO_3-N concentration of 0.7 and 1.6 mg/L in the RS and the NRS, respectively. The seasonal changes in NO_3-N levels of the river show the influence of the observed DC and PFs to the downstream NO_3-N pollution of the R (Mabaya et al., 2016c). PFs acted as a buffer between TPs and river reaches in controlling NO_3-N downstream pollution in an agricultural watershed, and the buffer effect was more pronounced in the RS. In summary, the observed NRS and RS NO_3-N results in the R seem to explain the significant role played by different land use interfaces in nitrate retention and the seasonal shift between hydrological and biogeochemical processes controlling nitrate dynamics in surface water resources.

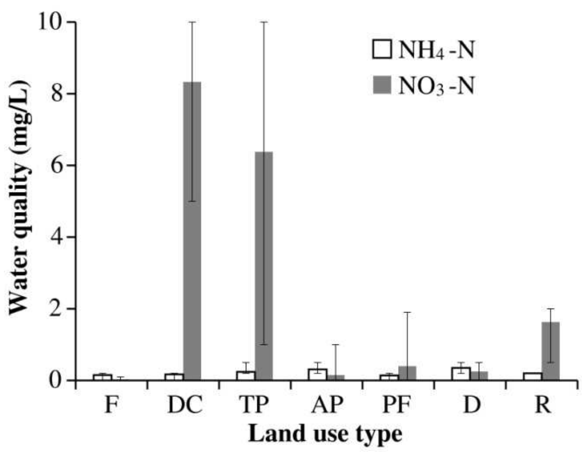

Figure 3-4 Mean observed NH_4-N and NO_3-N concentrations of water samples on forest (F), drainage channel (DC), tea plantation (TP), abandoned paddy field (AP), active paddy field (PF), irrigation pond (D) and river (R) land-use type during the non-rice growing season (NRS). The error bars show the maximum and minimum values of measured water quality item per land use type during the NRS.

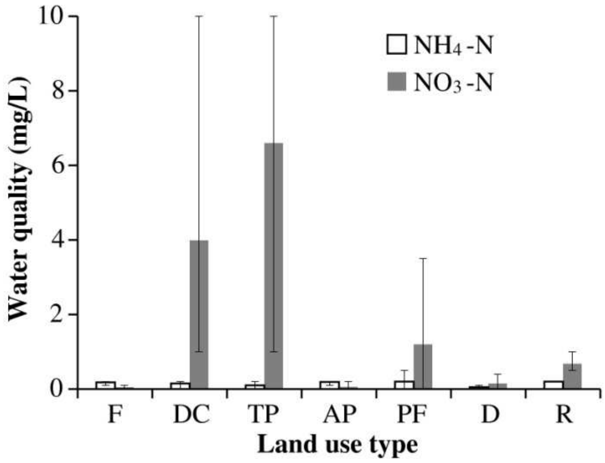

Figure 3-5 Mean observed NH_4-N and NO_3-N concentrations of water samples on forest (F), drainage channel (DC), tea plantation (TP), abandoned paddy field (AP), active paddy field (PF), irrigation pond (D) and river (R) land-use type during the rice growing season (RS). The error bars show the maximum and minimum values of measured water quality items per land use type during the RS.

3.5.2 Temporal and Spatial Reductions of NO_3-N in Wetland types

Figures 3-6 shows the observed mean spatial NO_3-N reductions for AP, PF and DC wetland types in Test 1 and Test 2 during the NRS and RS. The observed results showed that the rain events (as indicated by Test 2 measurements), temporarily increased NO_3-N reductions in all the wetland types and in all seasons. Spatial NO_3-N reductions between 69% and 75% of AP wetland type were observed in Test 1 and Test 2 measurements. No significant difference of the NO_3-N reduction ($p = 0.849$) in the NRS and ($p = 0.208$) in the RS between Test 1 and Test 2 measurements was observed. Spatial NO_3-N decrease was, however observed in AP from test point near TP_2 (in **Figure 3-3**) to the furthest test point down the slope. The decrease in Test 2 observed in APs in both seasons either could be attributed to rainfalls, which temporarily dilute nitrates, or increased anaerobic environment of APs which increases denitrification rates, or runoffs which simply washed away the nitrates from APs. While the source and the cause of the NO_3-N reduction in Test 2 observed in APs cannot be ascertained, the spatial NO_3-N decrease especially in Test 1 in both seasons indicate some considerable denitrification activity of APs.

For the PF wetland type, the temporal and spatial NO_3-N level changes were conducted in PF_2 (in **Figure 3-3**), which was receiving direct 5 mg/L and 10 mg/L NO_3-N contaminated direct inflow through DC during the NRS and through flume during the RS respectively. During the NRS, in Test 1 a 75% NO_3-N reduction from PF inflow inlet to the outlet was recorded. In Test 2, a 90% NO_3-N spatial reduction was observed. Overall, there was no significant change ($p = 0.288$) in the mean observed NO_3-N amounts from Test 1 to Test 2. During the RS, in Test 1 there was 82% NO_3-N reduction from PF inflow inlet to outlet. In Test 2, there was a 92% spatial reduction. Overall, there was no significant difference ($p = 0.154$) in the mean observed NO_3-N amounts from Test 1 to Test 2. The observed results showed that rain event insignificantly increase NO_3-N reductions of PFs in all seasons. Spatial NO_3-N reduction recorded in PFs was significantly higher ($p = 0.027$) in the RS than in the NRS. The increased NO_3-N reduction in the RS was likely due to increased denitrification rates and rice plant N uptake (Mabaya et al., 2016c). The increased ponding depths (Matsuno et al. 2006), increased summer temperatures (Vinod and Heuer, 2012), N fertiliser applications (Wang et al., 1993) and the rice plant stands in the RS (Ishii et al., 2011) appear to be the contributing factors to the significant NO_3-N reductions.

DC recorded a higher NO_3-N spatial and temporal reduction increase in RS as compared to NRS. During the NRS, almost all points recorded no change ($p = 0.468$) with the exception of only one reach in the DC that recorded a small NO_3-N reduction of 28%. However, during the RS there was a significant ($p = 0.004$) spatial NO_3-N reduction from pollutant point source (forest cliffs just below TPs) towards Yamakawa (R) confluence. This was due to dilution process by less NO_3-N contaminated discharges from PFs. Spatial NO_3-N reduction in the DC in Test 2 increased during the RS, due to frequent rain events that result in direct dilution by rainfall and indirectly due to increased dilution effect by drainage water from denitrifying PFs. Significant spatial NO_3-N reductions in the DC were observed during the RS when it rained, due to dilution by rainfall and indirectly due to increased dilution effect by draining PFs.

In summary the observed results show that rain events result in higher but not significant temporary NO_3-N reductions in wetland types in both seasons, except in DC wetland during the RS where it is significant due to dilution effect by PFs. The results confirm the findings of Billy et al. (2013) that nitrate fluxes and concentrations of artificial drainages in an agricultural watershed depends mainly on interface between hydrological conditions and land use type. While in their study they found that forest land-use type plays an important role in diluting artificial drains, likewise, paddy field land use types can also play a similar role in paddy-dominated watershed. Therefore, the current situation in the Imago area, though not optimal, is better than other tea growing areas because of the topo-sequence nature of green tea and paddy rice fields. The redesigning of DCs from intensive TPs or from any intensive agricultural upland fields to pass through PFs or linking the DCs of the intensive agricultural fields to the DCs of the PFs is therefore likely to result in significant decreases in NO_3-N concentration flows to the surrounding and downstream water resources due to dilution effect especially during the RS.

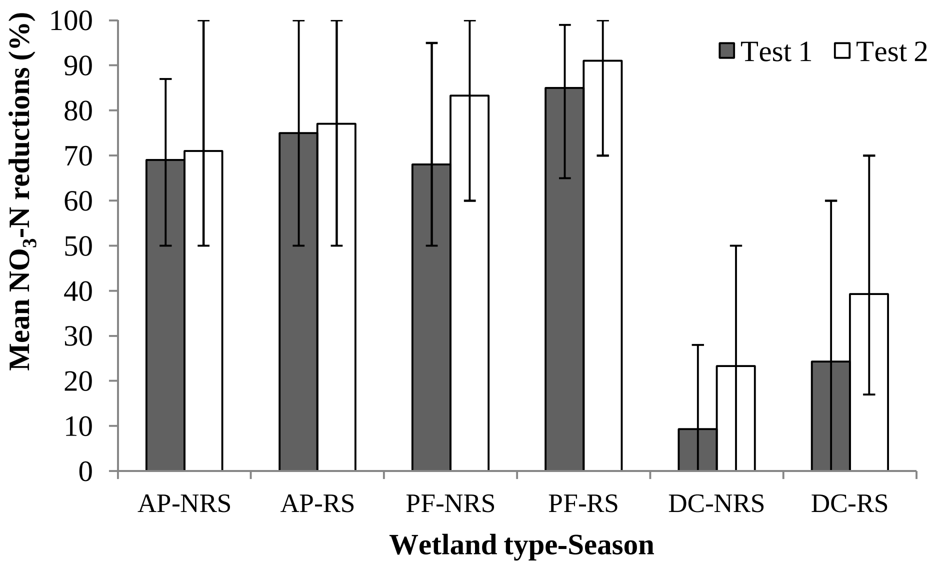

Figure 3-6 The observed mean spatial NO_3-N reductions of water samples on abandoned paddy field (AP), active paddy field (PF) and drainage channel (DC) wetland types in Test 1 and Test 2 during the non-rice growing season (NRS) and the rice growing season (RS). The error bars show the maximum and minimum NO_3-N reductions measured per wetland type. Test 1 measurements were conducted after no rain day and Test 2 measurements after rain day.

3.5.3 Estimated Model Parameters

Table 3-2 shows estimations of parameters p_i^* and σ_i of the robust optimal diversion model (5) in the NRS and the RS, respectively. Three and four reaches of DC from the upstream towards downstream ends recorded positive NO_3-N concentrations in the NRS and the RS, respectively.

Two reaches of APs recorded positive NO_3-N concentrations in both the NRS and the RS, respectively. Three and five cases of PF_2 in the NRS and the RS, respectively, confirmed positive NO_3-N concentrations. The results show that during the NRS, AP and PF wetland types have comparably high and nearly the same nominal NO_3-N reductions than DC wetland type, but the NO_3-N reductions deviation in the DC is the smallest. During the RS, nominal NO_3-N reductions of all wetland types are higher compared to their counterparts in the NRS. However, at the same time, APs and DC have higher deviations of nominal NO_3-N reductions indicating a bigger radius of uncertainty in NO_3-N reductions.

Table 3-2 Estimation of model parameters p_i^*, the average of the observed NO_3-N reductions, and σ_i, the standard deviation of the observed NO_3-N reductions, for drainage channel (DC), abandoned paddy field (AP) and active paddy field (PF) wetland types during the rice-growing season (RS) and the non-rice growing season (NRS).

Reach	Nominal NO_3-N reductions (%)					
	DC		AP		PF	
	NRS	RS	NRS	RS	NRS	RS
1	0	33	50	50	50	98
2	0	50	87	95	60	94
3	28	0			95	89
4		20				78
5						70
p_i^*	9	25	69	73	68	86
σ_i	16	21	26	32	24	12

3.5.4 Robust Optimal Distributions of Drainage Water to Wetland types

Table 3-3 shows computed results of robust optimal distributions for respective wetland types under different θ during the NRS and the RS respectively. The results show that choosing safety factor of $\theta = 3.2$ and $\theta = 3.6$ during the RS and the NRS, respectively, would result in all of the drainage water in the DC being diverted to the PFs and APs. As θ becomes larger, the model increasingly allocate to DC wetland type. Generally, in the NRS, optimal allocations to APs and PFs are almost similar per each safety factor chosen. This is somehow expected since the biogeochemical and hydrological processes in AP and PF wetland types are comparably similar, because, no irrigation and agronomic activities are carried in PFs during the NRS (Mabaya et al., 2016c). In contrast, the total drainage water allocations range to PF wetland type alone during the RS is 75-84%. During the RS the PFs are characterised with increased ponding depths from irrigation and rain, use of N fertilisers and plant uptake of N nutrients, which all lead to increased NO_3-N reductions (Freitag et al., 2005; Scheid et al., 2004). The inevitable increase in allocations to the PFs during the RS could lead to reduced amount of N fertilisers (and irrigation water) used in paddy rice production if properly managed (Mabaya et al., 2016a).

Figure 3-7 shows the resultant performance indexes, z, calculated as Equation (4) and the corresponding environmental risks, $v(\theta)$, calculated as $\sqrt{\sum_{i=0}^{n-1}\sigma_i^2 x_i^2}$, during the NRS and the RS respectively. The comparative results show that in overall, NO_3-N reduction function performs better during the RS than in the NRS. Choosing a safety factor of $\theta = 3.2$ and $\theta = 3.6$ during the RS and the NRS, would result in maximum performance indexes of 84% and 68% at a maximum operation risk level of about 11% and 18%, respectively. As θ becomes larger, the respective overall worst-case NO_3-N reductions decreases but the corresponding risks of operation also become smaller. In this regard, the robust optimal model becomes environmental risk-averse to possible malfunctioning of NO_3-N reduction processes in respective wetland types. The best trade-off robust safety factor θ for diversion of agricultural drainage water to APs, PFs and DC is chosen through observing behaviour of performance index and the worst-case NO_3-N reduction deviation under different θ chosen.

The best safety factors which results in best trade-off between large NO_3-N reductions and small NO_3-N reduction deviation for use in the RS and the NRS, would be $\theta = 3.5$ and $\theta = 4.5$, respectively. During the RS, at $\theta = 3.5$ the robust policy would result in performance index of 83% at environment risk of 11%. Likewise during the NRS, at $\theta = 4.5$ the policy would result in performance indexes of 58% at environment risk of 14%. The choice of θ for operation, at this stage, however is subject to decision maker's attitude towards risk (Mabaya et al., 2016c). Overall, the results show that the diversion of nitrate concentrated drainage water from upland intensive agricultural fields, like TPs in Japan, to the lowland PFs using the robust optimization approach is both environmentally sound and economically viable.

Table 3-3 Robust optimal allocations of unit discharge of NO_3-N contaminated agricultural drainage water to drainage channel (DC), abandoned paddy field (AP), and active paddy field (PF) wetland types under different θ, in the non-rice season (NRS) and the rice season (RS).

Safety factor θ	Optimal drainage water allocations x_i (%)					
	NRS			RS		
	DC	AP	PF	DC	AP	PF
3.2				0	16	84
3.5				2	15	83
3.6	0	54	46	2	15	83
4.0	8	50	42	3	14	83
4.5	15	46	39	8	13	79
5.0	19	44	37	8	13	79
6.0	26	41	34	11	12	77
7.0	29	39	32	12	12	76

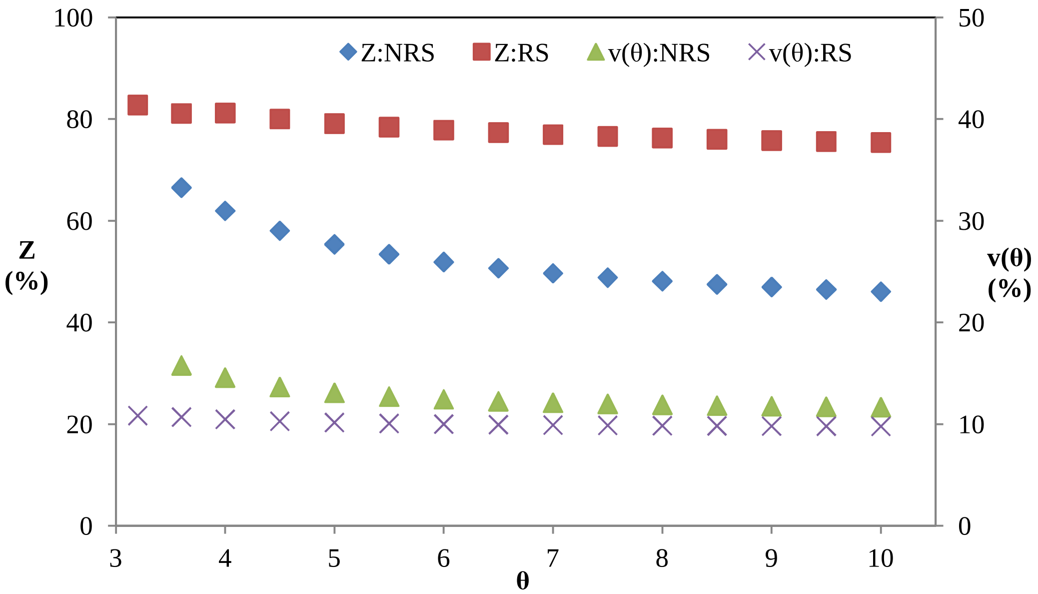

Figure 3-7 Robust optimal model characteristics: the performance indexes $Z:RS$ and $Z:NRS$, corresponding operation risk levels $v(\theta):RS$ and $v(\theta):NRS$ for the rice season (RS) and the non-rice season (NRS), respectively, under different safety factors (θ).

3.6 Conclusions

The water quality monitoring results at a small agricultural watershed dominated with tea plantations and paddy fields, shows that NO_3-N concentration of agricultural drainage water from tea plantations are still sufficiently high enough to cause water pollution to surrounding water resources throughout the year. On the contrary, NO_3-N contaminated drainage water from tea plantations, which flows into or through the abandoned and active paddy fields located on the valley bottoms of upland tea plantations, confirmed significant spatial NO_3-N reductions. The NO_3-N reduction of active paddy fields was significantly higher during the RS, whilst, NO_3-N reduction of abandoned paddy fields was comparably the same in both the RS and the NRS. Rain events in both the RS and the NRS temporarily increased NO_3-N reduction of abandoned and active paddy fields, and drainage channel. During the RS, the denitrified drainage water from active paddy fields, which drained into the drainage channel before it reaches the river, significantly diluted the NO_3-N concentration of drainage channel water flowing from tea plantations to the adjacent river via active paddy fields. Therefore, the current situation in the Imago agricultural watershed, where both tea and rice crops fields are in topo-sequence, though not optimal, is playing an important role in reducing NO_3-N pollution to adjacent and downstream rivers.

Diverting NO_3-N contaminated drainage water from tea plantations to abandoned and active paddy fields can further reduce NO_3-N pollution to surface water resources. However, the ratios of NO_3-N reduced in paddy fields are not distinct; therefore, in absence of hydraulic control system, implementation error uncertainties could result in further environment risks like nitrate leaching, emission of greenhouse N_2O gas and health hazard NH_3 gas. A robust optimal diversion model was developed to support the decision-making process for diversion of NO_3-N contaminated drainage channel water to paddy fields, in order to optimally reduce the amount of NO_3-N entering into and polluting the river. The application of the model to the study area shows that diversions to paddy fields are optimally maximized to reduce NO_3-N pollution to the adjacent river, averting environmental risk of possible malfunctioning denitrification processes in the respective paddy fields in both the NRS and the RS. During the NRS, operation of the model at a safety factor of $\theta = 4.5$ is recommended, which results in robust optimal drainage water allocations of 39% to active paddy fields and 46% to abandoned paddy fields, and the 15% to remain in the drainage channel. Likewise, during the RS, a safety factor of $\theta = 3.5$ is recommended, which results in robust optimal drainage water allocations of 83% to active paddy fields and 15% to abandoned paddy fields, and the 2% to remain in the drainage channel. Therefore, the diversion of agricultural drainage water from tea plantations to paddy fields using the robust optimal approach has potential to reduce N pollution in the surrounding water resources of the green tea plantations. The increased allocation of NO_3-N concentrated drainage water from tea plantations to active paddy fields (due to increased NO_3-N reduction activity) during the RS pose to reduce the cost of rice production through availing of free water and N nutrients to the rice crop. Therefore, the joint production of tea and rice using the robust optimal approach has potential to lead to sustainable agricultural production of the two crops, through reduced pollution and water demand pressure on the water resources, and reduced N-fertilizer cost for rice production. The robust optimal model as the decision support system for diversion of agricultural drainage water is also applicable for controlling agro-fertilizer pollution from other intensive agricultural systems, beside green tea plantations.

CHAPTER 4 Stochastic Optimal Control of Agrochemical Pollutants Loads in Reservoirs for Irrigation

4.1 Introduction

Global projections show that food production will need to double in order to feed the projected population of 9 billion by 2050 (Tomlinson, 2013). Annual cereal production will need to rise to approximately 3 billion tons (FAO, 2009). The demand for chemical fertilizers is, therefore, likely to continue to increase, not only to produce more food to meet the projected demand, but also to produce more biomass for energy purposes on a finite amount of land (Tallaksen et al., 2015). Nitrogen (N) is an essential macronutrient in cropping systems and so its use is increasing substantially. The global projected demand for N fertilizer is expected to rise to 135 million metric tons in 2030 (Xiang et al., 2015) from the current 110 million metric tons (Tallaksen et al., 2015), and the majority of N demand would occur in Asian countries (Tallaksen et al., 2015).

This ever-increasing rate of N fertilizer use in agricultural areas is, however, an environmental concern. In Japan, the intensive application of N fertilizers in green tea production has made tea plantations the highest N pollutant emitters to water bodies in agricultural watersheds (Oh et al., 2006). In the United States, nitrate concentrations in major rivers have increased three to tenfold, which is directly related to N fertilization as well as other human activities (Matson et al., 1997). As a result, many freshwater and marine environments are eutrophicating because of N (and phosphorous) lost in runoff or leaching from agricultural systems. Many agricultural areas are now characterized by incidences of nuisance algae blooms causing hypoxia and toxicity conditions in aquatic ecosystems leading to loss of fish, shellfish, and other aquatic life (Heisler et al., 2008). Underground water pollution associated with nitrate leaching has also become a concern in intensive agricultural areas (Eneji et al., 2013). The excessive irrigation water withdrawals in intensive agricultural areas have on other hand drastically reduced the assimilative capacities of water resources (Zhi et al., 2015).

As such, there have recently been concerted efforts to improve the sustainability of the use of N fertilizers. These efforts include efficiently using N fertilizers (Oh et al., 2006) at optimal application rates (Ali et al., 2015), as well as their use in conjunction with carbonates (Nakasone et al., 2002), super-absorbent polymers (Eneji et al., 2013), and biochar (Xiang et al., 2015). Other studies advocate for single cropping (Bacenetti et al., 2015), organic farming (Keyes et al., 2015), and gray-water footprinting of agricultural products (Zhi et al., 2015). In agricultural areas in which some of these measures have been implemented, some significant N reductions in surrounding water bodies have been observed (Hirono et al., 2009). However, some environment improvement efforts have suffered from concerns related to feeding the growing population. There is reluctance to continue adopting some agricultural clean production practices due to fears of reduced productivity (Luo et al., 2014). In Japan, further reductions in the use of N fertilizer in green tea production are not supported because they might lead to declines in the quantity and quality of tea produced (Hirono et al., 2009). This is despite the fact that, in some intensive tea-growing areas, runoff and drainage leachates continue to carry N pollutant loads high enough to pollute surrounding water bodies (Mabaya et al., 2016c).

Therefore, the current major challenge of agricultural science is to come up with technologies that can increase world food production with greater protection of the environment. In this Chapter, introducing environmental water technologies between intensive agricultural systems and adjacent rivers is hypothesized that it can significantly reduce N pollutant loading of downstream water bodies. There already have been research efforts in this direction. For example, Hefting et al. (2005) recommended placing forest buffers between agricultural systems and rivers. The previous Chapter proposes the diversion of nitrate-polluted agricultural drainage waters from intensive agricultural systems to paddy fields. Paradoxically, reservoirs used for irrigation in agricultural landscapes could also be an alternative to controlling the N nutrient loading from intensive agricultural systems to downstream surface waters. The catchment areas of such reservoirs usually consist of forests and mountainous areas, but some catchment areas include upland agricultural fields (Mabaya et al., 2015b). In such cases, the catchment areas are well-positioned to intercept a substantial amount of fertilizing nutrients and other pollutants from upslope agricultural systems (Powers et al., 2013). The buffering effects of these impoundments could be taken advantage of to influence the downstream riverine transport of fertilizing nutrients and pollutants. Numerous reservoirs are used for irrigation across the globe. The number of farmland water bodies is approximately 200,000 in Japan (Nakasone et al.,

2002) and 3.5 million in the United States (Powers et al., 2013). Therefore, the nutrient load that could be intercepted is quite substantial.

However, equally important is the in-pool water quality of these impoundments, as it affects other interests such as fishery, irrigation water use, and ecological water releases (Muñoz et al., 2006). Uncontrolled nutrient loadings into reservoirs could fuel eutrophication, which might lead to mass mortality of fish and other aquatic life (Smith et al., 1999). Since less attention is paid to the water quality aspect of the irrigation reservoirs, some reservoirs are increasingly becoming endangered due to long-term nutrient pollution. A typical example is mentioned in a study by Nakasone et al. (2002), who reported the total absence of aquatic life in a small irrigation reservoir in Japan due to strong acidity caused by long-term uncontrolled nitrate inflows from upslope green tea plantations. Moreover, ironically, if uncontrolled, long-term nutrient pollution of reservoirs would also pose a major threat to downstream aquatic and terrestrial ecosystems, in the case of the dam failure (Evans et al., 2000).

A novel approach to controlling agro-fertilizer nutrient loadings in reservoirs used for irrigation is presented in this chapter. The key objectives are i) to reduce the downstream surface water pollution from intensive agricultural systems, ii) to operate reservoirs to remain within N contaminant limits of the aquatic life therein, and iii) to safeguard the established irrigation values of reservoirs. The decision-making problem is formulated as a Markov decision process (MDP) model. The MDP model has been mathematically well established and has been applied in many areas (Ben-Tal et al., 2009), including those related to water resources (Lamond and Boukhtouta, 2002). The use of the MDP model in the present study is valid because the decision-making problem is both dynamic and stochastic. The stochastic natural water inflows and outflows of the reservoir, as well as transition equations of mass conservation, were modeled using Markovian stochastic processes. The MDP model used in the present study uses water quality and quantity norms to find the optimal operating policies for the reservoir. A reservoir used for irrigation in a study area in Japan that is prone to nitrate pollution from upslope green tea plantations is selected for application of the model. The optimal operation costs are calculated in monetary terms to comprehensively choose the optimal discharge rates and timings for the release of the reservoir inflows and outflows.

In this chapter, section 4.2 describes the formulation of the Markov decision process to find optimal policies for control of agro-pollutant loads in reservoirs for irrigation. Section 4.3 describes the governing equations of the model. Section 4.4 contains materials and methods illustrating how the formulated Markov decision process model could be applied to solve the nitrate pollution problems from green tea plantations. In section 4.5, the results of the study are stated and section 4.6 is the discussion. Conclusions of the study are given in last section.

4.2 Markov Decision Process Model

The irrigation reservoir is assumed to be operated using both water quality and quantity norms to optimally (i) control the reservoir agrochemical pollutant loads within the contaminant limits, (ii) maintain the reservoir storage above the environmental threshold, and (iii) meet the irrigation water demand. The reservoir operation method is assumed to be a dynamic decision-making problem involving a finite-state, finite-action stochastic system in which the system's dynamics are described by state transition probability distributions. An MDP solution is proposed to formulate the above-mentioned problem, with the goal of finding operation policies with a minimum worst-case expected value of a given cost function (Ben-Tal et al., 2009).

The storage level and the respective water quality index of the reservoir are taken to be a state variable $i \in X$, where the number of possible states $n = |X|$ is assumed finite. The reservoir $i \in X$ condition is assumed to be observed at regular finite time points $t \in T$ of the infinite decision horizon $T = \{0,1,2,...\}$. Depending on the $i \in X$ observed, the operator chooses a reservoir operation decision $a \in A$ from a finite set of all possible decisions $A = \{a_1,...,a_k\}$. If decision $a \in A$ is chosen for state $i \in X$, then cost $f(i,a)$ is incurred, and the condition state of the irrigation reservoir transitions to $j \in X$ according to $P_{ij}(a)$ (Ross, 1990), where $P_{ij}(a)$ are the transition probabilities under control action $a \in A$ at stage $t \in T$ from state $i \in X$ to state $j \in X$, which is expressed as follows:

$$P_{ij}(a) = P\left\{X_{t+1} = j \middle| X_t = i, a_t = a\right\} \tag{7}$$

The incurred costs $f(i,a)$ are assumed to be bounded by a positive real number M ($|f(i,a)| < M$), for $\forall i, \forall a$ with discount factor $\alpha \in (0,1)$. Thus, for any policy Π employed when the initial state is $i \in X$, the expected total discounted cost incurred is

$$V_{\Pi}^{\alpha}(i) = E_{\Pi}\left[\sum_{t=0}^{\infty}\alpha^{t} f(X_t, a_t) \middle| X_0 = i\right]. \tag{8}$$

Since the costs are bounded and $\alpha < 1$, $V_{\Pi}^{\alpha}(i)$ is also bounded, and thus equation (16) is well defined. Policy Π^* is said to be α-optimal if $V_{\Pi^*}^{\alpha}(i) = \inf_{\Pi} V_{\Pi}^{\alpha}(i)$ for $\forall i \in X$. The above principle of dynamic programming yields the Bellman equation

$$V_{\Pi^*}^{\alpha}(i) = \min_{a \in A}\left\{ f(i,a) + \alpha \sum_{j} P_{ij}(a) V_{\Pi^*}^{\alpha}(j) \right\}. \tag{9}$$

Accordingly, the corresponding optimal control policies Π^* for the operation of the irrigation reservoir under study is obtained by

$$\Pi^*(i) \in \arg\min_{a \in A}\left\{ f(i,a) + \alpha \sum_{j} P_{ij}(a) V_{\Pi}^{\alpha}(j) \right\}. \tag{10}$$

4.3 Governing Equations for the Storage and Water Quality Index Transitions

The water balance of the reservoir for irrigation, is represented as

$$\frac{\mathrm{d}V_t}{\mathrm{d}t} = \delta Q + Q_{\mathrm{cc}} - Q_{\mathrm{ir}} \tag{11}$$

where t is the time, V_t is the water storage volume of the reservoir at t, δQ is the uncontrollable water balance between inflow and outflow, Q_{cc} is the supplement discharge from an alternative water source, and Q_{ir} is the water withdrawal for irrigation from the reservoir. Here, δQ includes surface and subsurface runoff from the catchment areas, direct precipitation onto and evapotranspiration from the reservoir water surface, spillway outflows, and seepage losses. The mass balance of a water quality index in the irrigation reservoir at any given time t is represented as follows:

$$\frac{\mathrm{d}M_t}{\mathrm{d}t} = -zM_t + \delta F + F_{\mathrm{cc}} - F_{\mathrm{ir}} \tag{12}$$

where M_t is the mass of the water quality index, z is the coefficient of water quality index decay, δF is the uncontrollable flux balance of the water quality index, F_{cc} is the inflow flux of the water quality index from an alternative water source, and F_{ir} is the outflow flux of the water quality index due to irrigation water withdrawal. Then, the concentration C_t of the water quality index is governed by

$$\frac{\mathrm{d}C_t}{\mathrm{d}t} = -zC_t - \beta\frac{1}{V_t^2} + \gamma\frac{C_t}{V_t^2} + \frac{\delta F - C_t\delta Q}{V_t} + \frac{F_{cc} - C_t Q_{cc}}{V_t} + \frac{C_t Q_{ir} - F_{ir}}{V_t} \tag{13}$$

where $\beta=(\delta F\mathrm{d}t)(\delta Q\mathrm{d}t)$ and $\gamma=(\delta Q\mathrm{d}t)(\delta Q\mathrm{d}t)$. The coefficients β and γ are not negligible when δF and δQ are stochastic. Under the assumption that the reservoir under study is well mixed, $F_{ir}\approx C_t Q_{ir}$ is assumed. Thus, the temporal discretization over a time step Δt for equations (11) and (13) results in the following governing stochastic equations:

$$V_{t+\Delta t}=V_t+\Delta V+\int_t^{t+\Delta t}\left(Q_{\mathrm{cc}}-Q_{ir}\right)\mathrm{d}t \tag{14}$$

and

$$C_{t+\Delta t}=C_t+\Delta C+\int_t^{t+\Delta t}\left(-zC_t-\beta\frac{1}{V_t^2}+\gamma\frac{C_t}{V_t^2}+\frac{F_{cc}-C_tQ_{cc}}{V_t}\right)\mathrm{d}t \tag{15}$$

for storage and water quality index transitions in the reservoir, respectively, where ΔV and ΔC are random variables corresponding to $\int_t^{t+\Delta t}\delta Q\mathrm{d}t$ and $\int_t^{t+\Delta t}\frac{\delta F-C_t\delta Q}{V_t}\mathrm{d}t$, respectively. The integrals in equations (14) and (15) are constants in a stationary state. Therefore, based on these stochastic equations, the transition probabilities are statistically identified from the observed data series of V_t and C_t.

4.4 Materials and Methods

4.4.1 Description of Study Area

The MDP model is used to find the optimal policies for the control of agro-fertilizer nutrient pollutant loads of Imago reservoir (D_1) in the study area referred to as Imago area, extending over the Nunobiki hill and the adjacent valleys of Shiga Prefecture, Japan (34 96 N and 136 21 E). Imago area has a typical land use configuration that includes rainfed tea plantations (TPs) on hilltops and hill slopes, forests (Fs) on hill slopes, irrigation reservoirs (Ds), and abandoned paddies (APs) on upper valley bottoms, and active paddy fields (PFs) equipped with irrigation and drainage facilities in the middle valley bottoms, as shown in **Figure 4-1**. Yama River, which flows across the valley bottoms, also happens to be the main drainage channel of the study area. The total areas of Fs, APs, PFs, and TPs are 115 ha, 0.6 ha, 57.5 ha, and 34.3 ha, respectively. Imago reservoir was constructed in 1964 in order to irrigate the middle valley PFs. The reservoir has a capacity of 110,000 m^3, a water surface area of 1 ha, a catchment area of 20 ha, and a command area of 57.5 ha. The catchment area of Imago reservoir consists of Fs and TPs. Imago reservoir often receives water supplements from upstream Tongu reservoir (D_6) through a conveyance canal. Tongu reservoir is an earth reservoir built in 1965 for agricultural purposes and has a reservoir capacity of 320,000 m^3, a water surface area of 2 ha, and a catchment area of 0.9 km^2, which consists primarily of Fs.

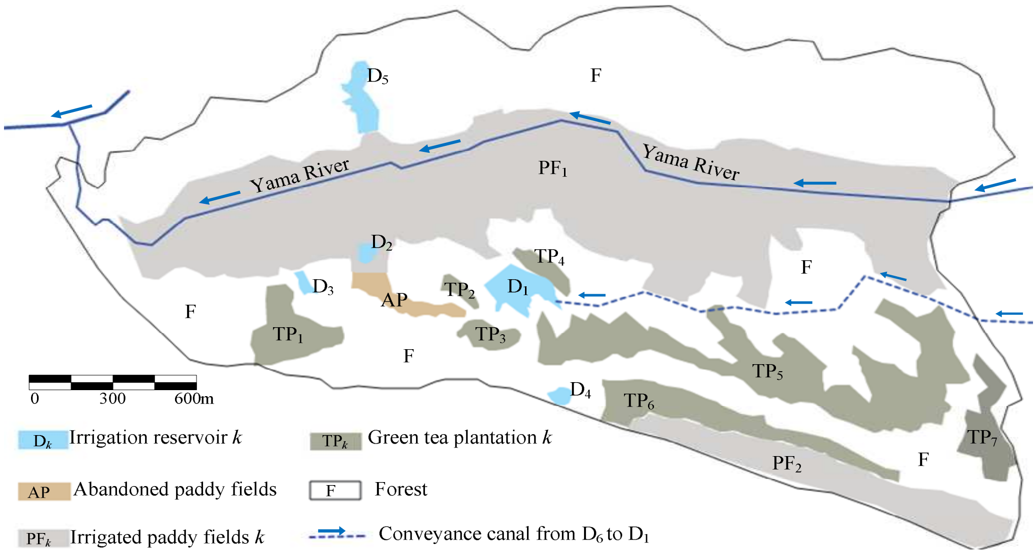

Figure 4-1 Schematic view of the land use configuration of the Imago agricultural area, which includes Imago reservoir (D_1), Higashi reservoir (D_2), Nishi reservoir (D_3), Fire Cistern pond (D_4), Nireno reservoir (D_5), and a conveyance canal from Tongu reservoir (D_6) to Imago reservoir (D_1).

4.4.2 Estimation of the Uncontrollable Water Balance Variables

An automatic weather observation system was installed in June 2014 within the Imago reservoir catchment area. Precipitation, humidity, air temperature, air pressure, and wind speed were continuously recorded in 10-minute intervals from June 2014 to November 2015. Assuming a uniform distribution of rainfall over the reservoir catchment area, the daily precipitation falling onto the reservoir surface area was directly transformed from the recorded weather data for precipitation. The daily evaporations from the reservoir were directly computed from the recorded weather data using the Penman equation for evaporation from an open water surface (Ritzema, 1994). Although there could be some uncertainty between the potential evaporation and the actual evaporation from Imago reservoir, the evaluation of the above-mentioned method revealed that the actual evaporation can be estimated with $R^2 \geq 0.93$ (Valipour, 2015). Moreover, the majority of the measured weather data for the study area were within the best weather conditions for use in this method (Valipour, 2014).

The Imago reservoir runoff catchment is ungauged. Therefore, the daily runoff inflows to the reservoir were estimated from the measured daily precipitation data using the Soil Conservation Service (SCS) Runoff Curve Number method (Al-Jabari et al., 2009). The reservoir lateral seepage losses were assumed to be negligible. Only the vertical daily seepage losses were considered and were estimated experimentally in the laboratory from samples of the clay loamy soil that forms the bottom of the reservoir (after puddling). The groundwater inflow was not taken into account, due to a lack of stream networks around the reservoir to account for base flow (Fowe et al., 2015).

4.4.3 Water Quality Monitoring

Water quality monitoring tests were conducted on the six irrigation reservoirs indicated in **Figure 4-1** as well as green tea plantations (TPs) and forests (Fs) of the Imago reservoir catchment area. The measured water quality indexes were nitrate-nitrogen (NO_3-N), nitrite-nitrogen (NO_2-N), ammonium-nitrogen (NH_4-N), and phosphate-phosphorous (PO_4-P). On-site water quality pack tests (Kyoritsu Chemical Check Lab Corp., Japan) were used. Measurements were conducted at least once per month from November 2013 to February 2015. The average and standard deviation for each water quality item were subsequently computed.

4.4.4 Identification of MDP Model Parameters

The identification of the operation decisions $a \in A$, state variables $i \in X$, transition probabilities $P_{ij}(a)$, and the incurred decision costs $f(i,a)$ for Imago reservoir is described.

4.4.4.1 Reservoir Operation Decisions Options

Four possible operation decisions $A = \{a_1, a_2, a_3, a_4\}$ for Imago reservoir (D_1) are shown in **Table 4-1**.

Table 4-1 Reservoir operation decision options $(a \in A)$ for Imago reservoir (D_1).

Decision	Parameters	Description
a_1	$Q_{ir} > 0, \quad Q_{cc} = 0$	Release irrigation water from Imago reservoir
a_2	$Q_{ir} = 0, \quad Q_{cc} > 0$	Introduce water supplements from Tongu reservoir to Imago reservoir
a_3	$Q_{cc} > 0 \Rightarrow Q_{ir} > 0$	Introduce water supplements first and irrigate later
a_4	$Q_{ir} > 0 \Rightarrow Q_{cc} > 0$	Irrigate first and introduce water supplements later

Table 4-2 Possible storage_NO_3-N $i \in X$ states for Imago reservoir at any given time categorized in terms of how they affect reservoir aquatic life and irrigated crop in the command area.

Storage volume $(\times 1{,}000\ m^3)$	NO_3-N (mg/L)			
	0-1	1-3	3-5	5-10
85-110	$i = 17$	$i = 18$	$i = 19$	$i = 20$
60-85	$i = 13$	$i = 14$	$i = 15$	$i = 16$
35-60	$i = 9$	$i = 10$	$i = 11$	$i = 12$
10-35	$i = 5$	$i = 6$	$i = 7$	$i = 8$
0-10	$i = 1$	$i = 2$	$i = 3$	$i = 4$

4.4.4.2 Defined Reservoir Storage and Water Quality Index States

The possible storage volume for Imago reservoir ranges from 0-110,000 m^3, and the NO_3-N concentration ranges from 0-10 mg/L. The environmental water volume threshold is set at 10,000 m^3. Above this threshold, volumes are categorized into accumulation ranges at 25,000 m^3 increments. The NO_3-N states are defined according to their effect on aquatic life, fish in particular. A study by Kincheloe et al. (1979) on the NO_3-N tolerance of fish eggs and fish fry revealed the following highest total mortality rates of 10% at 1.1 mg/L, 21% at 2.3 mg/L, and 59% above 4.5 mg/L. Therefore, a NO_3-N concentration below 1 mg/L is defined as *clean*, a NO_3-N concentration of from 1-3 mg/L is defined as *tolerable*, a NO_3-N concentration of from 3 to 5 mg/L is *intolerable*, and a NO_3-N concentration above 5 mg/L is *dangerous*. Therefore, 20 possible $i \in X$ storage_NO_3-N states for Imago reservoir are defined in **Table 4-2**.

4.4.4.3 Identification of Transition Probabilities

The Δt = 1 week transition probabilities, $P_{ij}(a)$, for Imago irrigation reservoir were derived from the governing equations given by Equations (14) and (15). The hydrodynamic and water quality (NO_3-N) monitoring measured data for the uncontrollable water balance variables for Imago reservoir was used as the principal data. The paddy rice-growing period (April 01 to September 30) was considered. The variables Q_{cc}, Q_{ir}, and F_{cc} vanish when no irrigation or water supplementation is carried out. Therefore, statistical procedures were first applied to the principal data of the storage transitions (V_t to $V_{t+\Delta t}$) in order to identify uncontrolled water storage changes (ΔV). Then, NO_3-N changes, including ΔC and the drift due to the integral, are hypothesized to have obeyed a probability law induced from the governing equation, given by equation (15). The worst-case scenario of the NO_3-N changes in the reservoir is assumed. The maximum NO_3-N observed during the period of water quality monitoring from TPs and Fs for the corresponding daily runoff fluxes into the reservoir is therefore considered. The daily rainfall flux was assumed to be 0.01 mg NO_3-N/L (Vet et al., 2014). The effect of the reservoir being in a dry or empty state was also taken into account through the relationship between β and γ, in which as γ becomes larger, β becomes smaller, or even negative. In the present study, the coefficient of decay, z, was considered to be negligible, as a result of water quality index monitoring. The transition probabilities when no irrigation or water supplementation was carried out were finally computed from ΔV and ΔC and considered as $P_{ij}(a_0)$.

Then, $P_{ij}(a_0)$ were transformed into $P_{ij}(a_1)$ by considering the subsequent effect of the variable Q_{ir}, which is the daily discharge required to meet the seven-day irrigation cycle crop water requirement for a 57.5 ha paddy rice crop. Likewise, $P_{ij}(a_0)$ were transformed into $P_{ij}(a_2)$ by considering the subsequent effect of the variable Q_{cc}, which is the water supplementary discharge from Tongu reservoir to Imago irrigation reservoir. The worst-case maximum-NO_3-N-pollution scenario for Q_{cc} is assumed for C_{cc}. The water supplement from Tongu reservoir is assumed to be implemented immediately after observing reservoir condition $i \in X$, followed by the irrigation activity. Therefore, $P_{ij}(a_2)$ were transformed into $P_{ij}(a_3)$ by considering the subsequent effect of Q_{ir} after Δt = 1 week. Likewise, $P_{ij}(a_1)$ were transformed into $P_{ij}(a_4)$ by considering the subsequent effect of Q_{cc} after Δt = 1 week.

4.4.4.4 Identification of Decision Costs

The costs incurred, $f(i,a)$, depend on the operation decision $a \in A$ applied to every observed state $i \in X$. Therefore, $f(i,a)$ include some or all of the following weekly costs: irrigation operation costs $(\mathrm{OM_{ir}})$, alternative water supplement costs $(\mathrm{OM_{cc}})$, irrigated crop potential value loss (RVL), aquatic potential value loss (AVL), and cost of downstream water pollution threat (DPT). Thus, the general decision cost is

$$f(i,a) = \mathrm{OM_{ir}} + \mathrm{OM_{cc}} + \mathrm{RVL} + \mathrm{AVL} + \mathrm{DPT}. \quad (16)$$

Here, $\mathrm{OM_{ir}} = \mathrm{W_{ir}} V_{\mathrm{ir}}$ and $\mathrm{OM_{cc}} = \mathrm{W_{cc}} V_{\mathrm{cc}}$, and $\mathrm{W_{ir}}$ and $\mathrm{W_{cc}}$ are the unit water costs multiplied by total water volumes V_{ir} and V_{cc}, respectively, for a 7-day irrigation cycle. Moreover, $\mathrm{W_{ir}}$ is estimated to be 0.025 US$/m^3 (Nickum and Ogura, 2010). The water supplementation unit cost is assumed to be $\mathrm{W_{cc}} \approx 2\mathrm{W_{ir}}$. $\mathrm{RVL} = \theta_{\mathrm{ir}}\mathrm{RV}$, where RV is the weekly irrigated crop monetary value in the command area, and θ_{ir} is the irrigation deficit coefficient. $\mathrm{RV} \approx$ US$14,600 (FAO, 2014). Here, $j \in X$ storage < 10,000 m^3 is assumed to indicate irrigation inadequacy. Thus, $\theta_{\mathrm{ir}} \approx 0.6$, otherwise $\theta_{\mathrm{ir}} \approx 0$.

$\mathrm{AVL} = \mathrm{AV}[\theta_{\mathrm{W}} + \theta_{\mathrm{N}}]$, where AV is the estimated aquatic value of the study irrigation reservoir, and θ_N and θ_{W} are the coefficients that represent the $j \in X$ state NO_3-N effect and the storage effect on AV, respectively. The fish yield is estimated to be 1,000 kg ha^{-1} year^{-1} (MRAG, 1995). Therefore, $\mathrm{AV} \approx$ US$1,500. The storage transition below the environmental water threshold (10,000 m^3) is assumed to indicate unsustainable water storage for aquatic life (Rolls et al., 2012). Therefore, $\theta_{\mathrm{W}} \approx 0.60$ is assumed for $j \in X$ storage < 10,000 m^3, otherwise $\theta_{\mathrm{W}} \approx 0$. The NO_3-N exposures limit the reproduction of aquatic life (Kincheloe et al., 1979). Therefore, for the $j \in X$ NO_3-N transition states of $C_{t+\Delta t} \le 1$ mg/L $\Rightarrow \theta_N \approx 0$, $C_{t+\Delta t} = 1.1 - 3.0$mg/L $\Rightarrow \theta_N \approx 0.10$, $C_{t+\Delta t} = 3.1 - 5$ mg/L $\Rightarrow \theta_N \approx 0.20$, and $C_{t+\Delta t} > 5$ mg/L $\Rightarrow \theta_N \approx 0.40$.

$\mathrm{DPT} \approx \mathrm{W_d V_d}$, where V_{d} is the volume and W_{d} is the corresponding unit cost of cleaner water required to dilute the $j \in X$ state to a tolerable 3 mg NO_3-N /L (Nakasone et al., 2002). Considering other water resource commitments in the Imago area, $\mathrm{W_d}$ is deliberately set at $\mathrm{W_d} \approx 2\mathrm{W_{cc}}$. Huang et al. (2006) first applied this replacement method.

4.5 Results

4.5.1 Uncontrollable Hydrodynamics of Imago Reservoir

Figure 4-2 shows the hydrodynamics of the observed daily precipitation, evaporation, and simulated runoff inflows of the Imago irrigation reservoir from June 2014 to November 2015. The rainfall for the study period totaled 2,130 mm, with the most rain falling during the summer/autumn period (April-October). The winter period (November-February) had the lowest rainfall. The peak rain months were characterized by storm events, and included June (186 mm), July (237 mm), August (159 mm), and September (158 mm). Due to the high clay content of catchment soils, the runoff generated by storm events was high. Accordingly, the source of water for Imago reservoir was predominantly agricultural runoff from TPs and Fs. Evaporation was highest during May-September and lowest during November-February.

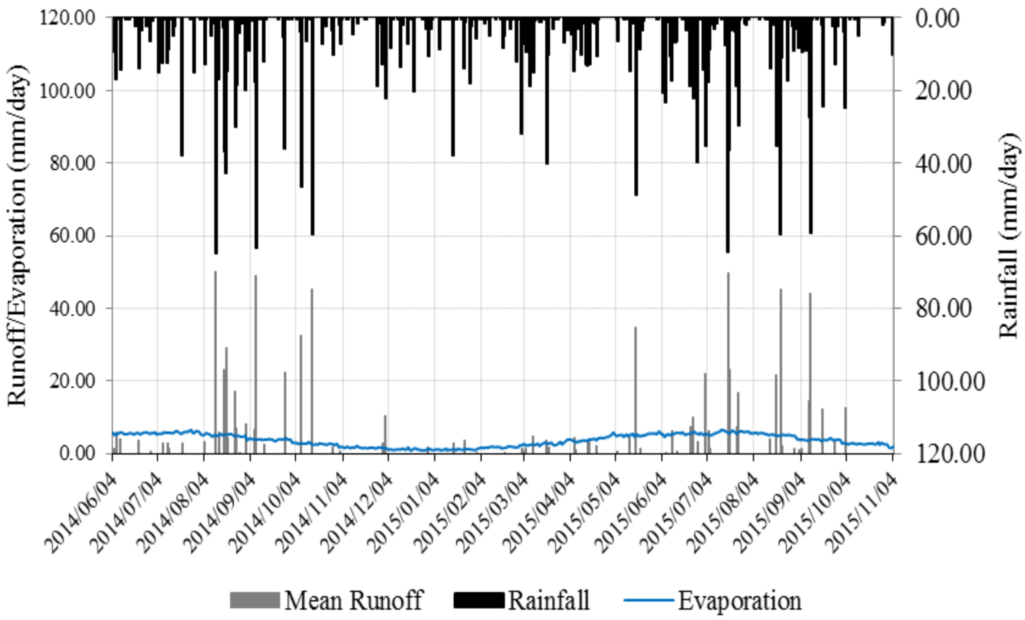

Figure 4-2 Observed direct daily rainfalls and evaporation, and simulated catchment runoff inflows in Imago irrigation reservoir from June 2014 to November 2015.

4.5.2 Water Quality Characteristics of Reservoirs and Land-uses

Figure 4-3 shows the mean observed concentrations of water quality indexes for the irrigation reservoirs, and the TP and F areas in the Imago area during the period between November 2013 and February 2015. NO_2-N was almost absent in all the reservoirs and other areas of land in the Imago area. Both NH_4-N and PO_4-P were small and were less than 1.0 mg/L in all of the measurements, with no significant differences among the reservoirs or other land-uses in the Imago area. The observed NO_3-N levels in the TPs were the highest among the land-uses. This was in sharp contrast to Fs, which exhibited the lowest NO_3-N levels. As noted in Section 4.5.1, the source of water of the reservoirs was predominantly from catchment runoff. Accordingly, the respective catchment areas of the reservoirs defined the observed NO_3-N levels of the irrigation reservoirs. Low NO_3-N levels were recorded in the reservoirs that had forested catchment areas (Tongu, Nireno, and Higashi). Likewise, the reservoirs, which include both F and TP areas in their respective catchment areas (Imago, Cistern, and Nishi), exhibited highest NO_3-N concentrations.

The NO_3-N levels of the Imago, Cistern, and Nishi reservoirs during the rice-growing season (RS) were also significantly lower than during the non-rice growing season (NRS). During the RS, observed NO_3-N levels decreased primarily due to dilution by cleaner water from Tongu reservoir, which was regularly introduced as supplement water for irrigation. When the irrigation period ends, water supplementation is stopped, and runoffs from TPs became dominant inflow source.

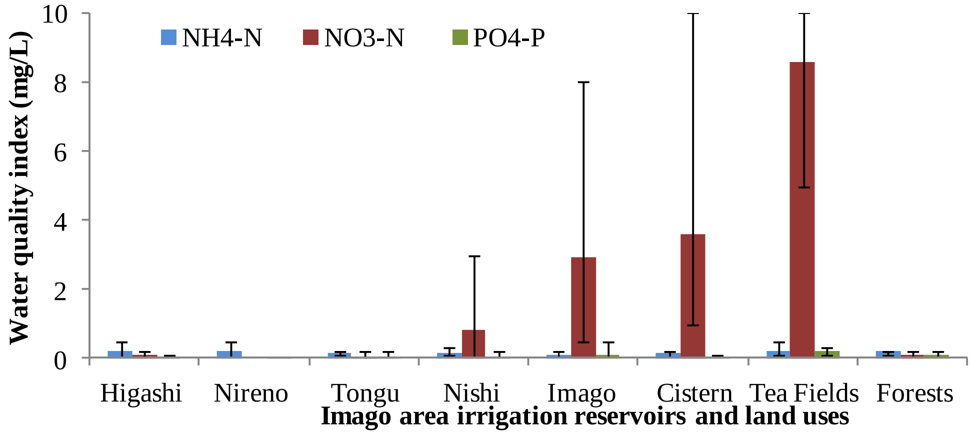

Figure 4-3 Mean water quality indices of irrigation reservoirs, tea plantations, and forests in the Imago area during the period of from November 2013 to February 2015. The error bars show the measured maximum and minimum values.

4.5.3 MDP Model Operation

The computed results of the MDP model operation for the Imago irrigation reservoir are presented in the following sections.

4.5.3.1 Identified Probability Transitions

Figures 4-4 to **4-7** show the Δt = 1 week time storage_NO_3-N transition probabilities, $P_{ij}(a)$, for Imago irrigation reservoir under control decision $a \in A$ (in **Table 4-1**) given by Equation (7). If the selected reservoir operation decision is to release irrigation water from Imago reservoir to the command area (a_1), the computed results of the $P_{ij}(a)$ matrix are likely to be as shown in **Figure 4-4**. When $i \in X$ storage ≤ 10,000 m^3, the reservoir practically dry or empty. When $i \in X$, storage > 10,000 m^3, the storage states transit to the next reduced storage states $j \in X$. In contrast, the NO_3-N pollutant levels would increase because agricultural runoff would be the dominant inflow type. The transition rate of the NO_3-N increase, however, decreases as the $i \in X$ storage_NO_3-N states increase.

The decision a_2, whereby water supplements from Tongu reservoir are introduced to Imago reservoir, would result in the $P_{ij}(a)$ transitions shown in **Figure 4-5**. The cleaner water supplements from Tongu reservoir become the dominant inflows. Therefore, the $i \in X$ states transit to larger $j \in X$ storage states, but reduced NO_3-N states. However, since the water supplementing volume is fixed for all $i \in X$ states, the dilution effect decreases as the $i \in X$ storage_NO_3-N states increase.

Figure 4-6 shows the effect of decision a_3: supplementing the Imago reservoir with water from Tongu reservoir before releasing the required irrigation water to the command area. **Figure 4-7** shows the effect of decision a_4: releasing irrigation water from Imago reservoir before introducing supplement water to the reservoir from Tongu reservoir. The results show that, with respect to storage, both a_3 and a_4 would result in approximately the same storage transition effect. The $j \in X$ transition volumes would predominantly remain the same as $i \in X$. Decision a_4, however, results in the maximum NO_3-N reduction. The dilution effect of decision a_4 also becomes less as $i \in X$ states increase.

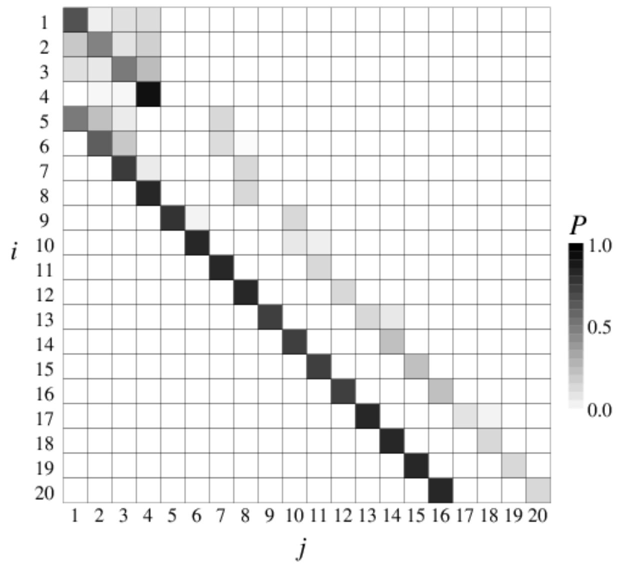

Figure 4-4 Storage_NO_3-N transition probability $P_{ij}(a_1)$ matrix after $\Delta t = 1$ week for Imago irrigation reservoir due to decision $a_{1,}$ when irrigation water is released from reservoir.

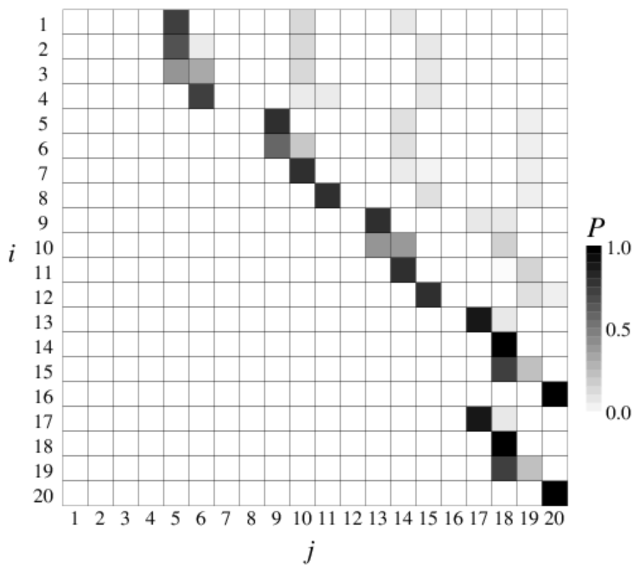

Figure 4-5 Storage_NO_3-N transition probability $P_{ij}(a_2)$ matrix after $\Delta t = 1$ week for Imago reservoir due to decision a_2, when water supplementation from Tongu reservoir is introduced to Imago reservoir.

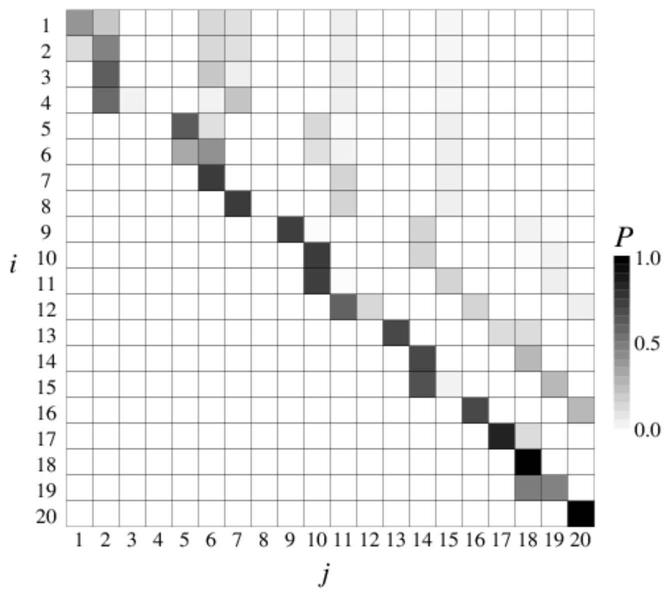

Figure 4-6 Storage_NO_3-N transition probability $P_{ij}(a_3)$ matrix after $\Delta t = 1$ week for Imago reservoir due to decision a_3, when water is supplemented from Tongu reservoir before irrigation water is released from Imago reservoir.

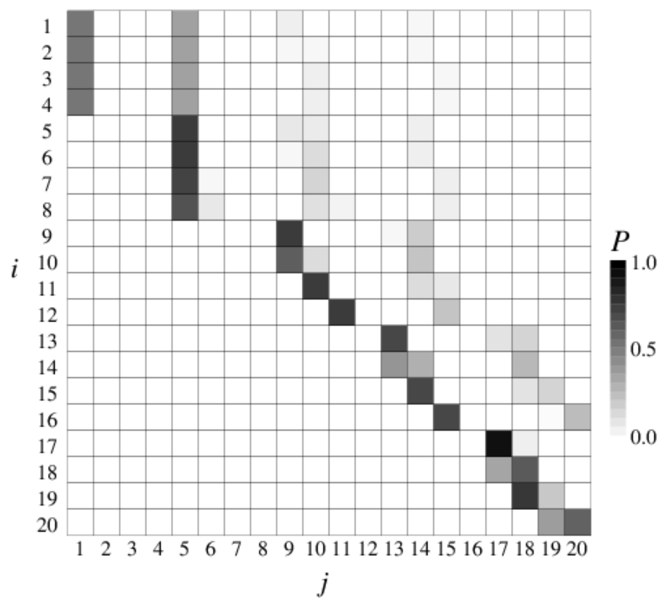

Figure 4-7 Storage_NO_3-N transition probability $P_{ij}(a_4)$ matrix after $\Delta t = 1$ week for Imago reservoir due to decision a_4, when irrigation water is released from Imago reservoir before introducing water supplements from Tongu reservoir.

4.5.3.2 Optimal Reservoir Operation Decisions

The operation of Equation (9) at a discount factor $\alpha = 0.9$ using the input data of $f(i,a)$ and the computed $P_{ij}(a)$ values resulted in the optimal costs $V_{\Pi^*}^{\alpha}(i)$ and the corresponding optimal operation policies Π^* (10), as shown in **Table 4-3**.

Table 4-3 Imago irrigation reservoir optimal operation policies Π^* and corresponding weekly optimal costs $V_{\Pi^*}^{\alpha}(i)$ in US$100 for 20 identified $i \in X$ storage_NO_3-N states.

	$i \in X$ storage_NO_3-N state																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
$V_{\Pi^*}^{\alpha}(i)$	77	79	82	87	23	23	25	26	12	21	31	47	9	20	35	59	8	21	37	70
Π^*	a_2	a_2	a_2	a_2	a_4	a_4	a_4	a_4	a_1	a_1	a_1	a_4	a_1	a_1	a_1	a_4	a_1	a_1	a_1	a_1

When the Imago reservoir storage volume is less than 10,000 m^3 (i = 1 to 4), regardless of the NO_3-N condition, the optimal operation decision is to introduce water supplements from Tongu reservoir to Imago reservoir (a_2). The environmental water threshold is fixed at 10,000 m^3. Therefore, the model prevents irrigation activity from occurring in order to protect the aquatic life in the reservoir. However, this leads to a reduction in value of the irrigated crops in the command area, making the cost to be highest when decision a_2 is the optimal decision.

When the Imago reservoir storage volume is in the range of 10,000 to 35,000 m^3 (i = 5 to 8), regardless of the NO_3-N state, the optimal operation decision is to release irrigation water from Imago reservoir to the command area before introducing cleaner water supplements from Tongu reservoir (a_4). In this regard, decision a_4 protects the value of the irrigated crop, while not only maintaining the water storage level above the environmental threshold but also keeping the water cleaner. However, at i = 12 to 16, where $NO_3\text{-N} > 5$ mg/L, a_4 is optimal because of its effectiveness in reducing NO_3-N pollution. Polluted irrigation waters that are first released from Imago reservoir facilitate effective NO_3-N load reduction in the reservoir by the subsequent cleaner water supplementation from Tongu reservoir.

For $i \in X$, when storage > 35,000 m^3 and NO_3-N < 3 mg/L, that is, i = 9, 10, 13, 14, 17, and 18, the optimal policy would be only to release the irrigation water from Imago reservoir (a_1).

This decision is justified because the reservoir water would be tolerably clean and irrigation activity would not cause the storage transition below environmental threshold (10,000 m^3). On the other hand, for $i \in X$, when storage > 35,000 m^3 and NO_3-N > 3 mg/L, that is, i = 11, 15, 19, and 20, decision a_1 is also optimal. This indicates that when NO_3-N > 3 mg/L, as the reservoir storage states approach full capacity, the introduction of cleaner water supplements is ineffective unless outflows that exceed the irrigation demand (V_{ir}) can be released first.

The computed results for the MDP model indicate that the model is capable of selecting optimal reservoir operation policies that maintain the reservoir storage level above the environmental threshold, minimize the reservoir NO_3-N pollutant load, and satisfy the irrigation water demand of the command area. Therefore, the developed MDP model supports the decision-making process to enhance the agricultural productivity while providing greater protection of the water environment.

4.6 Discussion

4.6.1 Nitrate Pollution Problem of Intensive Agricultural Areas

The NO_2-N level was almost zero, whereas the NH_4-N and PO_4-P levels were insignificant and were approximately the same for TP and F areas in the Imago area. This phenomenon appears to be common among Japanese agricultural watersheds, as it was also observed in an agricultural watershed in Gunma Prefecture, Japan (Ohrui and Mitchell, 1998). In contrast, the observed NO_3-N levels differed significantly among F and TP areas. Forested areas exhibited the lowest mean NO_3-N concentrations throughout the year. The results obtained herein are comparable to those obtained by Billy et al. (2013) in a watershed where forest land-use was dominant.

Notably, high mean NO_3-N levels were observed in the TPs throughout the year. The high and continuous NO_3-N levels in TPs are attributed to the frequent application of large amounts of N fertilizer to the crop throughout the year. The highest NO_3-N levels in TPs were measured during the irrigation season. The N fertilizer applied in winter and spring, which becomes nitrified, tends to remain in the surface soil until the rainy season, during which high precipitation leaches away the fertilizer (Hirono et al., 2009). Interestingly, green tea farmers in the Imago area were practicing the recommended N fertilizer application strategies, including the use of highly efficient N fertilizers at maximum annual application rates near 540 kg/ha in combination with organic fertilizers and carbonates as shown in **Chapter 3**. However, the NO_3-N pollution problem in TPs persisted. The reason for this may be that the optimal annual N application rate for green tea is still too high from an environmental point of view. However, further N reductions might affect the yield and quality of the green tea crop (Hirono et al., 2009). The reconciliation of these two demands, increased green tea production and greater protection of environmental water, is the subject of the present study.

4.6.2 Farm Reservoirs and Downstream Pollution Control

The source of water in the reservoirs used for irrigation in the Imago area was observed to be predominantly from catchment runoff. This appears to be a typical characteristic of farm dams. A similar study by Brainwood et al. (2004) indicated that direct precipitation generally comprises less than one-tenth of the total water input, while surface water, as runoff, can constitute nearly all of the water in a farm dam. Accordingly, the water quality dynamics of the respective reservoirs in the study area were defined by the hydrology of the land-use type. The NO_2-N level in all of the reservoirs was almost zero, while the NH_4-N level was very low, which is similar to the TP and F areas. The reservoirs that had a forested catchment area also exhibited very low NO_3-N levels. In contrast, the reservoirs that had catchment areas with both TP and F areas exhibited the highest NO_3-N levels, indicating that TPs were the source of NO_3-N pollution. The results, therefore, agree with the observation of Powers et al. (2013) that farm dams are well positioned to intercept a substantial amount of fertilizing nutrients from upslope agricultural systems. Consequently, from a larger perspective, the reservoirs influenced the riverine transport of fertilizing nutrients. A study by Mabaya et al. (2016a) revealed that the Yama River (in **Figure 4-1**), which flows across the valley bottoms of the study area, exhibited relatively low NO_3-N pollutant loads, despite the high pollutant loads observed in the TPs. Whereas Mabaya et al. (2016c) attributed this to the buffering role of the paddy fields, the reservoirs in the area appear to play an equally important role in dictating downstream surface water quality.

4.6.3 Water Quality Issues of Farm Dams

During the period of water quality monitoring in the Imago area, the authors observed that the NO_3-N levels in Imago reservoir were generally lower during the rice-growing season than during the non-rice growing season. During the irrigation period, the lesser-NO_3-N-polluted water supplements from Tongu reservoir to Imago reservoir significantly reduced the NO_3-N load in Imago reservoir through dilution. However, the positive water quality benefit of water supplementation was more incidental than intentional. When the irrigation period ended, water supplementation was also stopped. The focus of recent research on irrigation reservoirs appears to be the optimization of runoff capture and control water supply (Unami et al., 2015; Sample and Lin, 2014). Although this is commendable given the need to intensify agriculture, there is also a need to deliberately include water quality component in the optimization and integration approaches of irrigation reservoirs (Mabaya et al., 2016b).

4.6.4 Optimal Operation Policies of Reservoirs for Irrigation

The computed results indicate that when the downstream reservoir has nutrient pollution problems, the effective strategy is to irrigate before introducing cleaner water supplements. Releasing (polluted) irrigation water first facilitates subsequent cleaner water supplements to maximally dilute the remaining pollutant load. The strategy could prove beneficial in semi-arid and arid agricultural areas, where water supplementation is expensive. However, the strategy depends on the pollutant type. Releasing nitrate-polluted water to paddy fields provides N nutrients to the paddy rice crop (Mabaya et al, 2016a). However, if the water is saline or contains other pollutants that may be harmful to crops or the soil, first introducing cleaner water supplements is likely to be the optimal operation strategy (Muñoz et al., 2006). This could also be the case if the upstream water source was polluted (Xu et al., 2014).

Another important observation is that, as the reservoir storage level approaches full capacity and the pollution level reaches its maximum (NO_3-N > 5 mg/L), the MDP model selects only the irrigation activity. In the present study, the (cleaner) water supplement volume and irrigation water demand were fixed for every $i \in X$ storage_$\mathrm{NO_3}$-N state. Therefore, introducing a cleaner water supplement increasingly becomes less effective as the volume to be diluted increases. In order to address these shortcomings, intense research to identify how irrigation outflows and water supplement inflows could be varied, as well as the associated implications, is addressed in Chapter 5.

The present study is intended to complement established on-field efforts to manage agrochemical pollutants from intensive agricultural areas to downstream water bodies using farm dams. The proposed method can also be successfully used to improve the water quality of reservoirs endangered by long-term nutrient pollution. Furthermore, the proposed method can be used to improve environmental water productivity, especially when aquaculture production is intended to complement crop production. However, implementation of the method requires a careful analysis and an in-depth evaluation of different hydrologic periods and water quality index dynamics in order to produce representative probability transition simulations.

4.7 Conclusions

Hydrological analysis of Imago reservoir has shown that runoff is the predominant source of water for reservoirs used for irrigation. Reservoirs that have upslope intensive agricultural fields as part of their runoff catchment area intercept substantial amounts of NO_3-N pollutants via agricultural runoff. The MDP model developed in the present study deduces optimal policies for control of NO_3-N pollutant loads in reservoirs for irrigation.

The application of the MDP model to Imago reservoir shows that the model facilitates optimal control of NO_3-N pollutant loads within the allowable limits and maintains the reservoir storage above the fixed environmental threshold while satisfying the irrigation water demand of the command area. The optimal policy for all NO_3-N states of the reservoir when the storage level is below 10% is to introduce water supplements from the upstream reservoir. When the reservoir storage volume is in the range of 10 to 35% of active capacity, regardless of the NO_3-N state, irrigation water must be released from the reservoir before cleaner water supplements are introduced. When the reservoir storage volume is in the range of 35 to 85% of active capacity and when the NO_3-N concentration is less than 3 mg/L, releasing irrigation water is optimal. When the reservoir storage volume is in the range of 35 to 85% of active capacity and when the NO_3-N concentration is above 5 mg/L, irrigation water must be released before cleaner water supplements are introduced. However, when the reservoir storage volume is in the range of 85 to 100% of active capacity and when the NO_3-N concentration is above 5 mg/L, although the pollution level in the reservoir is maximum, the optimal policy is only to irrigate. When the reservoir is full, the introduction of cleaner water supplements becomes less effective unless the released outflow first exceeds the irrigation demand.

The newly developed MDP method supports decision-making processes for optimal control of agrochemical pollution from upslope agricultural systems into reservoirs for irrigation. The proposed method can be successfully used to maintain or enhance the productivity of intensive agricultural areas while providing improved protection of surrounding and downstream water resources from agrochemical pollution.

CHAPTER 5 Optimal Reoperation of Irrigation Ponds for Restoration of Aquatic Ecosystems in the Paddy Environments

5.1 Introduction

The Japanese paddy rural communities renowned of their unique history, old culture and ecologic space are facing a threat of collapsing. Japan paddy rice production processes are highly mechanized which makes the crop expensive to produce. Therefore, the free trade of agricultural products expected to be ushered in by Trans-Pacific Partnership (TPP) pact would make the Japanese farmers face difficulties to compete with cheaper rice imports, pushing many farmers to abandon the paddy cultivation (Katayama et al., 2015). However, the value of paddy environment in the Monsoon Asia goes beyond the provision of food and rice production profits. The rice-growing season, which tends to overlap with large amounts of early summer rains and typhoons that fall from June to October result in significant alleviation of potential large floods, groundwater recharges, water pollution reduction, soil erosion and landslides prevention, and biodiversity conservation in the paddy environments (Huang et al., 2006; Kim et al., 2006; Matsuno et al., 2006). The abandonment of paddy cultivation therefore poses a consequential threat to loss of the environment multifunctional attributes enjoined (Mabaya et al., 2015a). The losses are reported to be irretraceable, and their rehabilitation is difficult, takes a long time and is not possible to reactivate them all (Huang et al., 2006). There is, therefore, an urgent need for innovative water environment technologies that promote paddy environment profitability and sustainability, to keep the farmers in the paddy fields.

One possible solution is to introduce agricultural water management strategies that optimize the use of available water resources in the paddy environment. Introducing water environment management methods especially with the economies of scope in the paddy-rice production process would make it cheaper and efficient to provide the outputs jointly rather than separately, given the indivisibility of some inputs. For example, incorporating aquacultures in paddy irrigation schemes is logical, as they have positive technological interdependence with paddy rice production. The paddy irrigation schemes inherently possess biological environments favourable for aquaculture, while on the other hand, aquacultures have non-consumptive water use characteristic (Brugere et al., 2006). Accordingly, the increased efficient use of existing land and water resources in the paddy environment through integrated irrigation-aquaculture (IIA) offers an excellent opportunity for farmers to improve their global competitiveness, through shared water costs and added revenue from fish production. Farmers in China, India, Bangladesh and Vietnam (Phong et al., 2010) have employed IIA for centuries. IIA is also not new in Japan but simply a statement of logical approach. The oldest written record of rice-fish culture in Japan dates from 1844 although it is believed that it has been practiced long before that (Tamura, 1961). The common fish species reared in paddy irrigation systems for centuries are *Cyprinus carpio* (common carp) and *Carassius cuvieri* (white crucian carp). However, during the 1960s, which was the period of rapid economic growth in Japan, the number of paddy irrigation systems are reported to have increased exponentially (Matsuno et al., 2006). This indicates a huge potential for IIA development. Fish could be raised in irrigation reservoirs, but also within paddy fields, and irrigation and drainage canals.

Given the need to preserve the established irrigated paddy rice profits and avoid too much complexity in the water management of the irrigation schemes, emphasis on IIA development in this study is placed on the small irrigation reservoirs, also known as irrigation ponds in Japan (Hiramatsu et al., 2003) and irrigation tanks in India (Karthikeyan, 2010). Irrigation ponds are less capital-intensive (Karthikeyan, 2010), and the modifications required before incorporating fish in such reservoirs are also minor, and could be undertaken by the farmers (Brugere et al., 2006). In Japan, there are about 200,000 existing irrigation ponds, each with impoundment of mostly less than 5,000 m^3, which is about 11.4% of the total irrigation water impoundments (Hiramatsu et al., 2003; Nakasone et al., 2002). For the success of IIA development, the continuity of water supply or storage at specified water quality and turbidity in the ponds has to be guaranteed. However, the majority of irrigation ponds are characteristically small and shallow, not connected to major streams or other reservoirs, depending only on the rainfall and runoff in their own catchment areas (Karthikeyan, 2010). Therefore, temporal water shortages are a common phenomenon in most irrigation ponds. Fish production requires pond water storage to be retained above a certain minimum level at any given time. The mechanistic effects of low flow hydrology in the pond can negatively alter aquatic habitat conditions; consequently leading to mass mortality of fish and other aquatic life (Rolls et al., 2012). On the other hand, adequacy and timeliness of irrigation water supply has to be ensured for a good rice crop harvest. Therefore, conflicts on water use between the two production entities can arise during the periods of water insufficiency (Mabaya et a.l, 2015a).

To improve the water supplies, the irrigation ponds can be connected to either the upstream reservoirs and/or irrigation system by feeder canals, and can receive irrigation return flows. However, the strategy can be constrained when the water supplements contains high loads of agro-pollutants. Many of alternative water sources in agricultural regions suffer from long-term pollution, due to considerable amounts of fertilisers and pollutants intercepted in runoffs from upslope agricultural fields (Powers et al., 2013). Like any other aquatic habitat, IIA ponds require an adequate water quality to sustain aquatic life, therein. Temperature, dissolved oxygen (DO), nitrogen (N), phosphorus (P), salinity, pH and other associated water quality requirements tend to vary for each of the life stages and activities of fish. At conditions outside the specified range, fish tend to grow at slow rates, becoming vulnerable to predation, diseases, and mass mortality (Campbell et al., 2001). Nevertheless, the temporal water shortage characteristic of the irrigation ponds, necessitate the need to develop strategies that optimize the use of available water resources in the paddy environment, even with lesser water quality.

This study proposes an optimal method that considers the respective water quantity and quality requirements of fish and paddy rice crop in the operation of the irrigation ponds intended for IIA establishment. An irrigation pond is selected for IIA development in a study area in Japan where IIA is not currently practiced. The daily water balance of the selected pond was monitored for a period of five years to understand its detailed water storage dynamics. The water quality dynamics of the pond as well as of other ponds in the study area were also monitored for a period of more than two years. Field surveys were also conducted on established IIA ponds in Bangladesh, to comprehend the actual intense practice thereof. A Markov decision process (MDP) was formulated and applied to find the optimal policies for operation of the study irrigation pond using water quantity and quality norms, with the aim to establish a successful IIA. All the costs for optimal operation of the pond are calculated in monetary terms to choose the optimal schedules.

5.2 Materials and Methods

5.2.1 Description of Study Area

The MDP model is applied to find the optimal operation policies for restoration of fish ecosystems and preservation of the established paddy irrigation value benefits in Higashi irrigation pond (D_2), which is in a study area called Imago, extending over the southern part of Shiga prefecture, Japan (34 96 N and 136 21 E). **Figure 5-1** shows the schematic view of the study area, including Higashi irrigation pond and Imago dam.

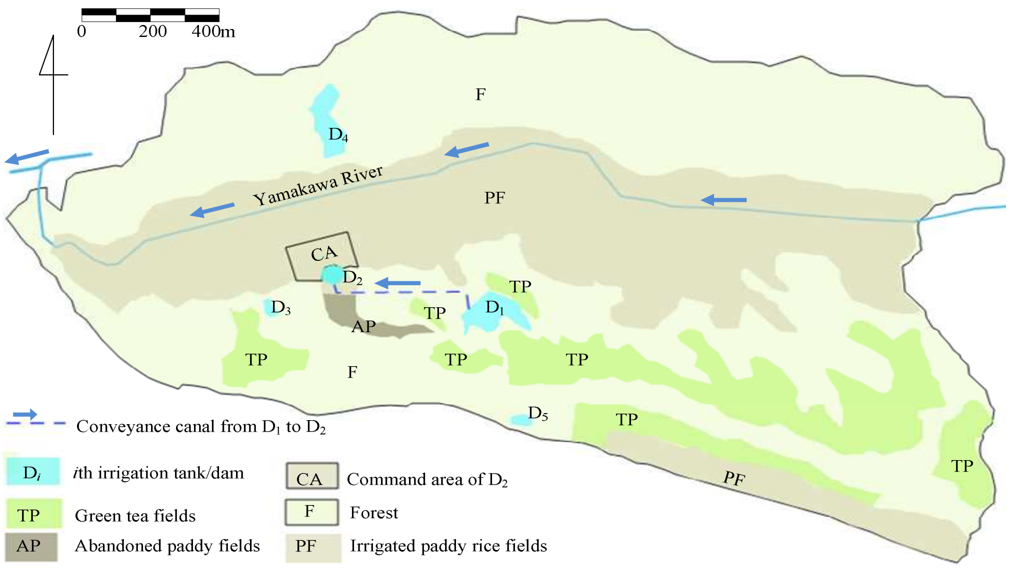

Figure 5-1 Schematic view of the land use configuration of the Imago agricultural area, which includes Imago reservoir (D_1), Higashi reservoir (D_2), Nishi reservoir (D_3), Fire Cistern pond (D_4), Nireno reservoir (D_5), and a conveyance canal from Tongu reservoir (D_6) to Imago reservoir (D_1).

Higashi irrigation pond is a rainwater harvesting earth pond primarily built to irrigate a command area of 5 ha paddy rice fields. The pond has maximum surface area of 3,060 m^2, maximum water depth of 1.21 m, capacity of 3,000 m^3, catchment area of about 7.2 ha, and two major inlets of runoff inflows on the western and southern sides. The pond catchment area consists of paddy fields and forest landuses. The Higashi irrigation pond is considered for IIA development, however due to its small capacity, the larger Imago dam (D_1) on the upstream, is planned to supplement the waters in the pond to provide a continuity of water supply and storage. Imago dam has the reservoir capacity of 110,000 m^3 and the catchment area of 20 ha, which consists of green tea fields and forest landuses. IIA is not currently being practiced in Imago area. In order to comprehend the actual intense practice thereof, field surveys on water quality management and fish abundance were conducted in a typical agricultural area of Bangladesh where IIA has been employed for years in many excavated ponds adjacent to paddy fields and households. The area is referred to as Godashimla area, which extends around the coordinates 24 51 N and 89 58 E, with 14 ponds surveyed out of hundreds.

5.2.2 Markov Decision Process Model

The future operation of Higashi irrigation pond is to be operated using both water quality and quantity norms, focused on developing and maintaining a sustainable environment for IIA. The pond operation methodology is assumed a dynamical decision-making problem involving finite-state, finite-action stochastic system where the system's dynamics are described by state transition probability distributions. An MDP solution is proposed to formulate the above-mentioned problem, with the goal to find operation policies with minimum worst-case expected value of a given cost function (Ben-Tal et al., 2009). The storage level and the respective NO_3-N level of Higashi irrigation pond are taken to be a state variable $i \in X$ where the number of possible states $n = |X|$ is assumed finite. The pond $i \in X$ condition is to be observed at regular finite time points $t \in T$ of the infinite decision horizon $T = \{0,1,2,...\}$.

Depending on the $i \in X$ observed, the operator chooses a decision $a \in A$ from a finite set of all possible decisions $A = \{a_1,...,a_k\}$. If the decision $a \in A$ is chosen for the state $i \in X$, then the cost $f(i,a)$ is incurred and the condition state of the irrigation pond transit to the next according to $P_{ij}(a)$ (Ross, 1990), where $P_{ij}(a)$ are the transition probabilities under control action $a \in A$ at the stage $t \in T$ from the state $i \in X$ to the state $j \in X$ expressed as

$$P_{ij}(a) = P\{X_{t+1} = j \mid X_t = i, a_t = a\} \quad (17)$$

The incurred costs $f(i,a)$ are assumed to be bounded by a positive real number M, such that $|f(i,a)| < M$ for $\forall i, \forall a$ with a discount factor $\alpha \in (0,1)$. Thus, for any policy Π employed when the initial state is $i \in X$, the expected total discounted cost incurred is

$$V_{\Pi}^{\alpha}(i) = E_{\Pi}\left[\sum_{t=0}^{\infty} \alpha^t f(X_t, a_t) \middle| X_0 = i\right] \tag{18}$$

given that policy Π is employed. Since the costs are bounded and $\alpha < 1$, $V_{\Pi}^{\alpha}(i)$ is also bounded and thus equation (18) is well defined. The policy Π^* is said to be α-optimal, if $V_{\Pi^*}^{\alpha}(i) = \inf_{\Pi} V_{\Pi}^{\alpha}(i)$ for $\forall i \in X$. The above principle yields the Bellman equation

$$V_{\Pi^*}^{\alpha}(i) = \min_{a \in A}\left\{ f(i,a) + \alpha \sum_j P_{ij}(a) V_{\Pi^*}^{\alpha}(j) \right\} \tag{19}$$

Accordingly, the corresponding optimal operation control policies Π^* for Higashi irrigation pond were obtained by

$$\Pi^*(i) \in \arg\min_{a \in A}\left\{ f(i,a) + \alpha \sum_j P_{ij}(a) V_{\Pi^*}^{\alpha}(j) \right\} \tag{20}$$

5.2.3 Governing Equations for Transitions

The storage dynamics of the reservoirs are usually estimated using the general water balance equation where all the stochastic variables are observed over a long period for the better estimation as in the study of Fowe et al. (2015). However, the water balance of small reservoirs like irrigation ponds can also be practically estimated within acceptable accuracy if the water storage level dynamics are known in detail. In this study, the water balance of Higashi irrigation pond, is represented as

$$\frac{\mathrm{d}V_t}{\mathrm{d}t} = \delta Q + Q_{\mathrm{cc}} - Q_{\mathrm{ir}} \tag{21}$$

where t is the time, V_t is the water storage volume of Higashi irrigation pond at t, δQ is the uncontrollable water balance between inflow and outflow, Q_{cc} is the supplement discharge from Imago dam to Higashi irrigation pond via the proposed conveyance canal, and Q_{ir} is the water withdrawal for irrigation from Higashi irrigation pond. δQ includes surface and subsurface runoff from the catchment areas, direct precipitation onto and evapotranspiration from the pond water surface, spillway outflows, and seepage losses. Likewise, the mass balance of a water quality index in the pond at any given time t is represented as

$$\frac{\mathrm{d}M_t}{\mathrm{d}t} = -zM_t + \delta F + F_{\mathrm{cc}} - F_{\mathrm{ir}} \tag{22}$$

where M_t is the mass of the water quality index, z is the water quality index decaying coefficient, δF is the uncontrollable flux balance of the water quality index, F_{cc} is the inflow flux of the water quality index via the conveyance canal, and F_{ir} is the outflow flux of the water quality index due to water withdrawal. Then, the concentration C_t of the water quality index is governed by

$$\frac{\mathrm{d}C_t}{\mathrm{d}t} = -zC_t - \beta\frac{1}{V_t^2} + \gamma\frac{C_t}{V_t^2} + \frac{\delta F - C_t\delta Q}{V_t} + \frac{F_{cc} - C_t Q_{cc}}{V_t} + \frac{C_t Q_{ir} - F_{ir}}{V_t} \tag{23}$$

where $\beta = (\delta F \mathrm{d}t)(\delta Q \mathrm{d}t)$ and $\gamma = (\delta Q \mathrm{d}t)(\delta Q \mathrm{d}t)$. The coefficients β and γ are not negligible when δF and δQ are stochastic. The pond is shallow and well mixed, therefore $F_{ir} \approx C_t Q_{ir}$ can be assumed. Accordingly, the temporal discretization over a time step Δt of equations (21) and (23) results in the following respective governing stochastic equations (24) and (25) for storage and water quality index transitions in the pond:

$$V_{t+\Delta t} = V_t + \Delta V + \int_t^{t+\Delta t} \left(Q_{\mathrm{cc}} - Q_{ir}\right) \mathrm{d}t \tag{24}$$

and

$$C_{t+\Delta t} = C_t + \Delta C + \int_t^{t+\Delta t} \left(-zC_t - \beta\frac{1}{V_t^2} + \gamma\frac{C_t}{V_t^2} + \frac{F_{cc} - C_t Q_{cc}}{V_t}\right) \mathrm{d}t \tag{25}$$

where ΔV and ΔC are random variables corresponding to $\int_t^{t+\Delta t} \delta Q \mathrm{d}t$ and $\int_t^{t+\Delta t} \frac{\delta F - C_t \delta Q}{V_t} \mathrm{d}t$, respectively. The integrals in (24) and (25) are constants in a stationary state. Therefore, based on these stochastic equations, the transition probabilities are statistically identified from observed data series of V_t and C_t.

5.2.4 Water Balance Monitoring

The hydrological variables such as rainfall, and reservoir water levels in the Higashi irrigation pond were continuously recorded from August 2000 to September 2006 using an automatic observation system. Rainfall was continuously measured using an automatic tipping rain gauge. The pond water levels h_{t} were measured at 5 min intervals using an automatic water level recorder installed at the walls of the pond. The general equation of the average daily volume of water in the pond V_{t} (m^3) per measured average water level h_{t} (m) on a given time t is based on the previous work of Kirihata et al. (2001) and is formulated as:

$$V_{\mathrm{t}} = 113.1 h_{\mathrm{t}}^2 + 2350 h_{\mathrm{t}} \tag{26}$$

5.2.5 Water Quality Monitoring

Water quality items NO_3-N, NO_2-N, NH_4-N, PO_4-P and pH of the water samples from 5 irrigation reservoirs in the Imago area including Higashi irrigation pond and Imago dam were measured using simplified on-site water quality pack tests (Kyoritsu Chemical Check Lab Corp, Tokyo, Japan). The measurement period was from November 2013 to February 2015, once per month. Using the same measurement method, the water quality indexes including DO were periodically measured from January 2012 to December 2015 in Godashimla area of Bangladesh, targeting ponds, which are considered as established IIA ponds, as well as alternative water sources like canals and boreholes. Information on the abundance of fish in each of the water quality tested ponds was also collected.

5.2.6 Identification of MDP Model Parameters

The identification of the irrigation pond operation decisions options $a \in A$, transition probabilities $P_{ij}(a)$, and the incurred decision costs $f(i,a)$ for the development and maintenance of a sustainable IIA environment in Higashi irrigation pond is described in this section.

5.2.6.1 Pond Operation Decision Options

Table 5-1 shows four (4) water resources management decision options $A = \{a_0, a_1, a_2, a_3\}$ identified for the development and maintenance of a sustainable environment for IIA in the Higashi irrigation pond.

Table 5-1 Water Management Decision Options $a \in A$.

Decision	Parameters	Description
a_0	$Q_{ir} = 0, \quad Q_{cc} = 0$	Do nothing
a_1	$Q_{ir} > 0, \quad Q_{cc} = 0$	Release irrigation water from Higashi pond
a_2	$Q_{cc} > 0, Q_{ir} = 0$	Introduce water supplements from Imago reservoir
a_3	$Q_{cc} > 0 \Rightarrow Q_{ir} > 0$	Supplement and then irrigate

5.2.6.2 Defined Pond Storage and Water Quality Index States

The $i \in X$ states of the water storage and the water quality index (which are NO_3-N levels in this Chapter) for Higashi irrigation pond are identified to be the following 12 states in **Table 5-2**.

Table 5-2 Higashi irrigation pond possible storage_NO_3-N states.

Storage volume (m^3)	NO_3-N (mg/L)		
	0-1	1-3	> 3
> 3000	i = 10	i = 11	i = 12
2000-3000	i = 7	i = 8	i = 9
1000-2000	i = 4	i = 5	i = 6
0-1000	i = 1	i = 2	i = 3

5.2.6.3 Processing of Principal Data

The observed water level data h_t for the Higashi irrigation pond of each irrigation season (April1- September10) of respective year from 2000 to 2005 was retrieved from the mass data. The actual days when irrigation activity was executed were identified, and the corresponding h_t data thereof was removed from the retrieved data. The remained h_t data was assumed to be exclusively related to uncontrollable water balance between inflow and outflow (δQ). A total of 21 time series h_t data of 5 minutes intervals was able to be extracted and transformed into dynamical volumes V_t by applying Equation (26). The successive daily water storage changes for uncontrollable water balance (ΔV) were then computed. Accordingly, the corresponding successive monthly changes of the NO_3-N observed during the period of water quality monitoring in the Higashi irrigation pond (ΔC) were computed, and likewise were also assumed to be influenced exclusively by uncontrollable hydrological variables. Assuming no significant change in the NO_3-N dynamics between the period of water balance monitoring and of water quality monitoring, ΔC were paired with ΔV.

5.2.6.4 Computation of Transition Probabilities

The transition probabilities $P_{ij}(a)$ were derived from the governing Equations (24) and (25). The variables Q_{cc}, Q_{ir}, and F_{cc} vanish when the decision $a \in A$ is a_0. Therefore, firstly statistical procedures were applied to the principal data of the storage transitions (V_t to $V_{t+\Delta t}$) to identify the uncontrolled water storage changes (ΔV). Then, it was hypothesized that NO_3-N changes including ΔC and the drift due to the integral obeyed a probability law induced from the governing Equation (25). The effect of dry or empty state of the pond was taken into account through the β and γ effect, as γ becomes larger while β becomes smaller or even negative. The decaying coefficient z was considered to be negligible as a result of the water quality index monitoring. The transition probabilities $P_{ij}(a_0)$ were then computed from those two sources.

The variable Q_{ir} was assumed to be the daily discharge required to meet the daily crop water requirement of 5 ha paddy rice crop in a seven days irrigation cycle, transforming $P_{ij}(a_0)$ into $P_{ij}(a_1)$. The supplementary water from Imago dam to Higashi irrigation pond was assumed to be sufficiently large in quantity to fill it until its full capacity from any initial storage state with the maximum level of pollution. Therefore, the worst case scenario, where the maximum NO_3-N measured in Imago dam during the period of water quality observation, was assumed for C_{cc}, and $P_{ij}(a_2)$ was computed accordingly. For the decision option, a_3, the water supplement from Imago dam was assumed to be implemented immediately after observing pond condition $i \in X$, followed by irrigation activity (Mabaya et al.,2015a). Therefore, $P_{ij}(a_3) = P_{ij}(a_1)P_{ij}(a_2)$.

5.2.6.5 Identification of Decision Costs

Depending on the decision $a \in A$ applied for every $i \in X$ observed state, the costs incurred $f(i,a)$ include some or all of the following costs: irrigation operation and maintenance costs $[\mathrm{OM_{ir}}]$, Imago dam water supplement costs $[\mathrm{OM_{cc}}]$, irrigated paddy rice value potential loss $[\mathrm{RVL}]$, and fish potential value loss $[\mathrm{FVL}]$. Therefore, the general decision costing $f(i,a)$ is formulated as:

$$f(i,a) = \mathrm{OM_{ir}} + \mathrm{OM_{cc}} + \mathrm{RVL} + \mathrm{FVL} \tag{27}$$

where the operation and maintenance costs are represented as $\mathrm{OM_{ir}} = \mathrm{W_{ir}}V_{\mathrm{ir}}$ and $\mathrm{OM_{cc}} = \mathrm{W_{cc}}V_{\mathrm{cc}}$ with respective unit water costs $\mathrm{W_{ir}}$ and $\mathrm{W_{cc}}$ multiplied by respective water volumes V_{ir}

and V_{cc} in 7 days irrigation cycle. $\mathrm{RVL}=\theta_{ir}\mathrm{RV}$ where RV is the irrigated paddy rice monetary value in the command area and θ_{ir} is the irrigation deficit coefficient that depicts storage effect of the $j \in X$ state on RV. $\mathrm{FVL} = \mathrm{FV}[\theta_{W} + \theta_{N}]$ where FV is the estimated fish value in the Higashi irrigation pond (after restocking); θ_N and θ_W are the coefficients that respectively depicts the NO_3-N effect and storage effect of each of the $j \in X$ state on FV.

In principle, Japan rice farmers pay about 500 US$/ha for irrigation operations and maintenance costs (Nickum and Ogura, 2010). Therefore, assuming total seasonal crop water demand of 20,000 m^3/ha, W_{ir} and W_{cc} were approximated 0.025 US$/$m^3$.

In Japan, the average yield of the irrigated paddy rice is estimated 6.0 tonnes/ha (World Bank, 2014), the average rice price is 2,500 US$/tonne (FAO, 2014), and the unit cost of production 9,900 US$/ha (Nickum and Ogura, 2010). Given the command area of Higashi irrigation pond of 5 ha, the estimated total irrigated rice value is US$27,000. Assuming the crop cycle of 20 weeks for paddy rice, the weekly $\mathrm{RV} \approx \mathrm{US\$1{,}350}$. The $V_{t+\Delta t} < 1000\ \mathrm{m}^3$, for $a \in A$ which involves irrigation activity, are assumed to indicate not enough water released for irrigation. Considering the average yield of 2.5 tonnes/ha for the rainfed paddy rice in South East Asia (Redfern et al., 2012), therefore with no irrigation, irrigated paddy rice yield is approximated to be reduced to 60%. Accordingly, for $V_{t+\Delta t} < 1000\ \mathrm{m}^3 \Rightarrow \theta_{ir} \approx 0.60$, otherwise $\theta_{ir} \approx 0$.

This study's supposition is that fish juveniles shall be initially re-stocked for recruitment in Higashi irrigation pond, and later on fish populations would be left to expand through natural reproduction. The fish are assumed would be extensively farmed. A 10% water volume of pond capacity (300 m^3) is assumed to be totally reserved for fish, wherein a minimum potential fish yield of 10 kg/m^3 shall be maintained (Woynarovich et al., 2012).Thus the total potential fish value in the Higashi irrigation pond of US$15,000 is estimated. Considering the rice-growing season, the weekly fish potential value $\mathrm{FV} \approx \mathrm{US\$750}$. The minimum threshold of pond water volume for fish production at any given time is set at $V_{t+\Delta t} \geq 1000\ \mathrm{m}^3$. Therefore, the $V_{t+\Delta t} < 1000\ \mathrm{m}^3$, are assumed to be correlated to mortality of fish stocks, due to associated disturbances in the aquatic habitat (Rolls et al., 2012). Accordingly, at $V_{t+\Delta t} < 1000\ \mathrm{m}^3 \Rightarrow \theta_{w} \approx 0.65$ otherwise $\theta_{w} \approx 0$. On the other hand, basing on the Kincheloe et al. (1979) study, the NO_3-N exposures are assumed would limit survival of fish populations due to impairment of reproductive processes. Thus, for $j \in X$ NO_3-N states of $C_{t+\Delta t} \leq 1$ mg/L $\Rightarrow$ $\theta_N \approx 0$; $C_{t+\Delta t} = 1.1 - 3.0$mg/L $\Rightarrow \theta_N \approx 0.25$; and $C_{t+\Delta t} > 3.0$ mg/L $\Rightarrow \theta_N \approx 0.40$.

5.3 Results and Discussions

5.3.1 Higashi Irrigation Pond Hydrodynamics

Figure 5-2 shows the daily pond water levels and the corresponding daily precipitation observed in the Higashi irrigation pond, for the hydrological year 2004, as a typical representative of all other years of water balance monitoring. The pond hydrodynamics show that the irrigation period (April to September) as compared to non-irrigation period (October to February) of every year is associated with excessive irrigation water drawdowns, and in some cases, the water is withdrawn until near empty storages states.

The study of Hiramatsu et al. (2003) reported some presence of fish species in the Higashi irrigation pond which included *Oryzias latipes* (Japanese rice fish), *Palaemon paucidens* (freshwater prawn), and *Rhinogobius* sp. (freshwater gobies). However, the assessed commercial value of aquatic products in the pond during the period 2013-2015, showed that it was almost negligible (Mabaya et al., 2015a). The loss of fish value in the pond is linked to the loss of preferred aquatic habitat caused by the successive antecedent critical low water levels in the irrigation seasons (Rolls et al., 2012). Fish are reported to be more sensitive to low water level events during the summer (irrigation) period since it is the period when fish naturally have higher productivity and dispersal than winter period (Harvey et al., 2006). Therefore, the associated rapid drawdowns accompanied with unsustainable low water levels during the irrigation period in the Higashi irrigation pond could have resulted in the successive loss of fish value. In 2005 and in 2013 the pond was emptied (Mabaya et al., 2015a). Such incidents when the pond completely dries up are linked to aquatic biotic extinction, leaving the pond with a negligible fish brood stock for recruitment (Davey et al., 2006). The reduced volumes and depths of aquatic habitat are also linked to significant negative water quality levels like reduced dissolved oxygen (DO) and increased water temperatures which again lead to mass mortality of aquatic biota (Miller et al., 2007). These responses are more direct to macro invertebrates and fish (Dewson et al., 2007). Fish juveniles are highly affected by the loss of preferred habitat especially when it involves smaller impoundments like irrigation ponds (Rolls et al., 2012).

Therefore, to restore a healthy functioning fish ecosystem in the Higashi irrigation pond for IIA development, fish juveniles have to be initially restocked for recruitment. An additional water source to guarantee a continuity of water supply to the pond is required, to keep the pond water storage level at any given time above the specified minimum threshold level of 1000 m^3.

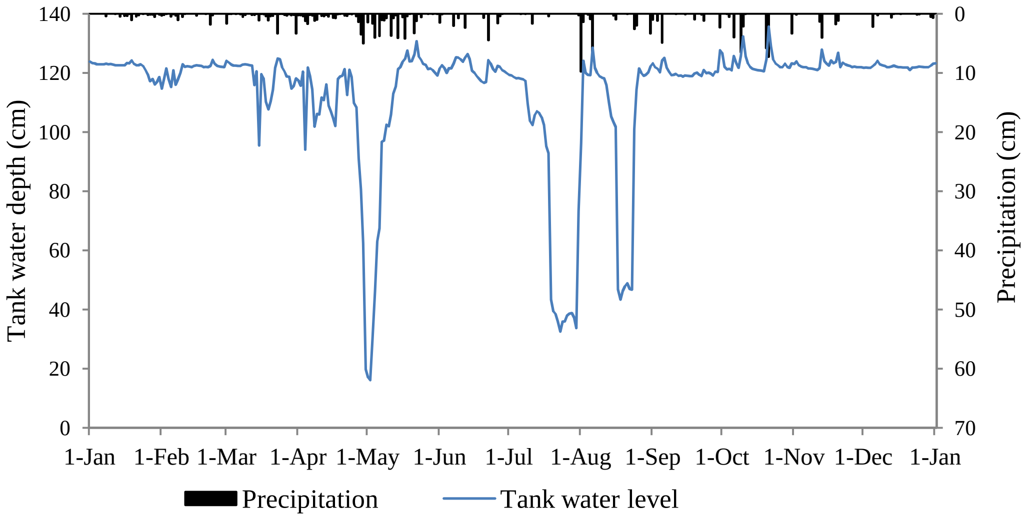

Figure 5-2 Observed direct daily rainfalls and evaporation, and simulated catchment runoff inflows in Imago irrigation reservoir from June 2014 to November 2015.

5.3.2 Water Quality Characteristics of Irrigation Ponds

Figure 5-3 and **Figure 5-4** show the mean observed water quality indexes concentrations and pH of water sources in Imago area of Japan, and Godashimla area of Bangladesh respectively. In Imago area (**Figure 5-3**), NO_2-N was almost absent in all the ponds, while NH_4-N and PO_4-P were very small and below 0.5mg/L in all measurements and with no significant difference among the respective reservoirs. The mean pH observed was between 7 and 8. However, the observed NO_3-N level in the ponds was defined by the land-use type of their respective catchment areas, which is a typical characteristic of farm dams (Brainwood et al., 2004). Low NO_3-N levels were recorded in the ponds with runoff catchment areas of forest and paddy fields land use type (Higashi and Nireno). The irrigation ponds, which include both forest and green tea fields runoff catchments (Imago, Cistern and Nishi), recorded higher NO_3-N concentrations.

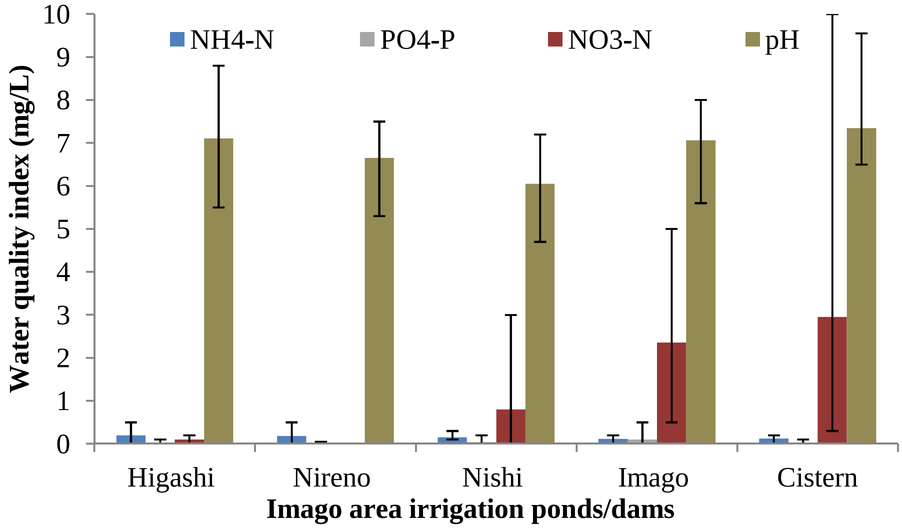

Figure 5-3 Mean water quality indices of irrigation reservoirs, tea plantations, and forests in the Imago area during the period of from November 2013 to February 2015. The error bars show the measured maximum and minimum values.

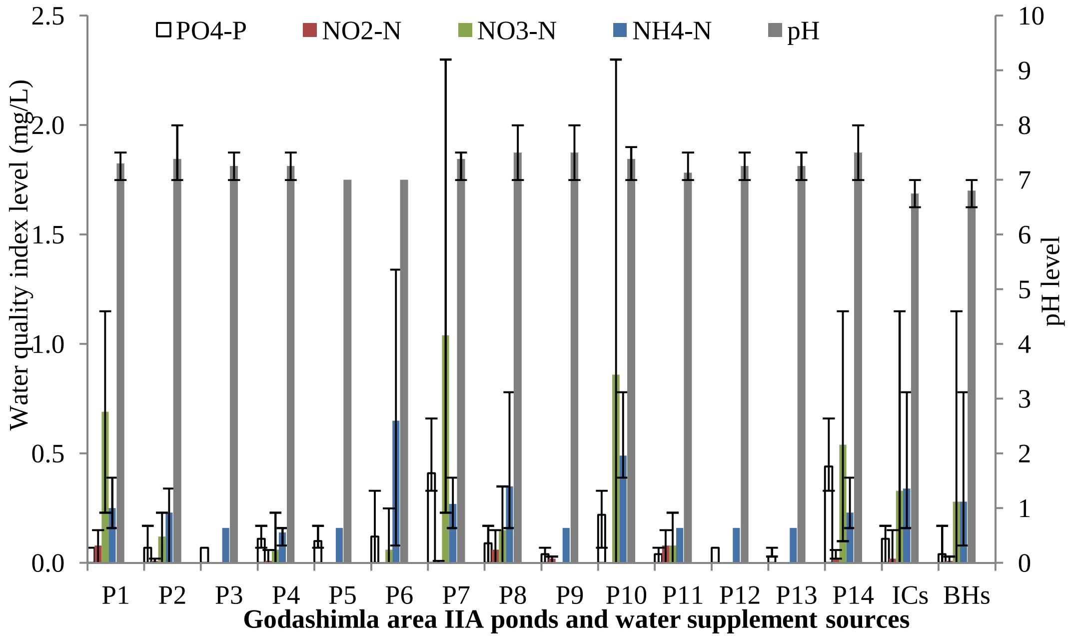

Figure 5-4 Mean observed water quality indexes of IIA ponds (P1-P14) and water supplement sources: irrigation canals (ICs) and boreholes (BHs), in Godashimla area, Bangladesh from January 2012 to May 2015. Error bars show the measured maximum and minimum values.

In Godashimla area (**Figure 5-4**), some NO_2-N were measured in all the IIA ponds, irrigation canals and boreholes, where the average was below 0.1 mg/L. The average NH_4-N was nearly the same and below 0.50 mg/L in all ponds and other water sources, except in IIA pond number 6 (P6) where a maximum of 1.3 mg/L was measured. NO_3-N was less than 1 mg/L in many IIA ponds except in pond P7 and P10, and in some irrigation canals and boreholes where it fluctuated to maximums of 1.1-2.3 mg/L. PO_4-P was below 1 mg/L in all measurements. The pH measurements for all the water sources were between 7 and 8. The results show that phosphorous, with which the local soil is fertile, is not a serious problem for IIA in Godashimla area. The pH measurements also show that it was not a constraint for successful IIA production.

However, the survey results from Godashimla area supported the literature reviewed correlation between the nitrogen compounds and fish production. Ammonia is toxic if allowed to accumulate in fish production systems. At high concentration, it becomes lethargic leading to fish to fall into coma and die, and even at lower concentration it has sub-lethal effects such as reduced growth, poor feed conversion and reduced disease resistance (Durborow et al., 1997; Randall and Tsui, 2002). High NH_4-N also often indicates that nitrite concentration (which is more toxic) may soon arise (Durborow et al., 1997). While it is difficult to be precise about the risk of ammonia toxicity to fish production as it depends also on water pH and temperature; the maximum allowable for fish culture is usually 1 mg/L at pH of 7.5 and temperature of 30°C (EIFAC, 1984). Thus, the observed NH_4-N levels in Bangladesh were within tolerable range, except only for pond P6 which was continuing to paddy fields to practice rice-fish culture. On the other hand, the nitrite levels are recommended to be always be zero in the ponds, as very small nitrite levels at low chloride content could prove harmful if exposure is prolonged (Hargreaves and Tucker., 2004). EIFAC (1984) proposes that the average NO_2-N should not exceed 0.2 mg/L where chloride concentration is below 1mg/L for fresh water fish. Above that, fish becomes more susceptible to brown blood disease causing affected fish to suffocate, which leads to mass mortality (Kroupova et al., 2005). The maximum NO_2-N concentration of 0.15 mg/L observed in the Godashimla IIA ponds is below the harmful level.

On the other hand, while nitrate is far less toxic than ammonia and nitrite, it has long-term effects on general health, growth and breeding ability of fish. A study of Kincheloe et al. (1979), on tolerance of fish eggs and fish fry observed the following worst total mortality rates directly linked to nitrate exposures: 10% (at 1.1 NO_3-N mg/L); 21% (at 2.3 NO_3-N mg/L); and 59 % (above 4.5 NO_3-N mg/L). Higher nitrate concentration also indicates a nitrite threat, as some of nitrite originates from uncompleted reduction of nitrate through the activity of phytoplankton (EIFAC, 1984). The fish population observed in ponds P7 and P10 show that they were dominantly of *Tilapia nilotica* (Nile tilapia), which is an introduced specie. This was quite different from the other 12 ponds, where various carp species such as *Cirrhinus cirrhosis* (mrigal), *Labeo rohita* (ruhi), and *Catla catla* (Indian carp) were abundant as well as smaller *Cyprinidae* and *Channidae* species. The null hypothesis that fish abundance is independent of NO_3-N level is therefore, rejected with the *p*-value 1/91 of the Fisher's exact test.

The water quality characteristics of Higashi irrigation pond in Imago area show that at the present they are within acceptable specified ranges for fish production. However, unlike the alternative water supplement sources in the Godashimla area, which have acceptable water qualities, the nitrate levels of Imago dam, which is to provide water supplements to Higashi irrigation pond are above tolerable levels. Thus, on implementation, the NO_3-N levels for Higashi irrigation pond are likely to fluctuate to intolerable levels. Therefore, water quality management strategies have to be incorporated to control NO_3-N levels low enough for the development and maintenance of a sustainable IIA in the Higashi irrigation pond.

5.3.3 MDP Model Operation

5.3.3.1 Identified Transition Probabilities

Figures 5-5 to **5-8**, show the respective $\Delta t = 1\,\text{week}$ time storage_NO_3-N transition probabilities $P_{ij}(a)$ for the Higashi irrigation pond, under each operation decision $a \in A$ (identified in **Table 5-1**) from each state $i \in X$ (identified in **Table 5-2**) to the state $j \in X$, expressed as (25).

$P_{ij}(a_0)$ matrix in **Figure 5-5** shows that the decision a_0 (doing nothing), would result in the $j \in X$ states remaining almost the same as their $i \in X$ state counterparts, but with some likelihood for a small increase in storage and decrease in NO_3-N level of the pond, due to pond inflows from direct rainfall and less polluted runoffs from forest catchment area. The $P_{ij}(a_1)$ in

Figure 5-6 matrix shows that the decision to withdraw irrigation water would highly influence states to transit to reduced states predominantly in terms of storage levels. On the other hand, the $P_{ij}(a_2)$ matrix in **Figure 5-7** shows that the decision to water supplement Higashi irrigation pond until its full capacity with water from Imago dam would predictably result in the states transiting to full storage states. Since Imago dam water supplements are sufficiently NO_3-N polluted, then it means, NO_3-N would also transit to higher NO_3-N states. The $P_{ij}(a_3)$ matrix in for the decision to water supplement followed by the irrigation activity would results in the $P_{ij}(a_1)P_{ij}(a_2)$ effect as shown in **Figure 5-8**. As a result, the storage states would transit to higher states but lesser than $P_{ij}(a_2)$, but the NO_3-N states would transit to higher states but lesser than $P_{ij}(a_2)$.

The transition matrices results therefore show that each of the operation decisions would influence the storage and NO_3-N transitions differently depending on the state of the irrigation pond. Consequently, each of the operation decisions applied and the resultant states have a different influence on the productivity of both fish recruited in the pond and the paddy rice crop in the command area of the pond.

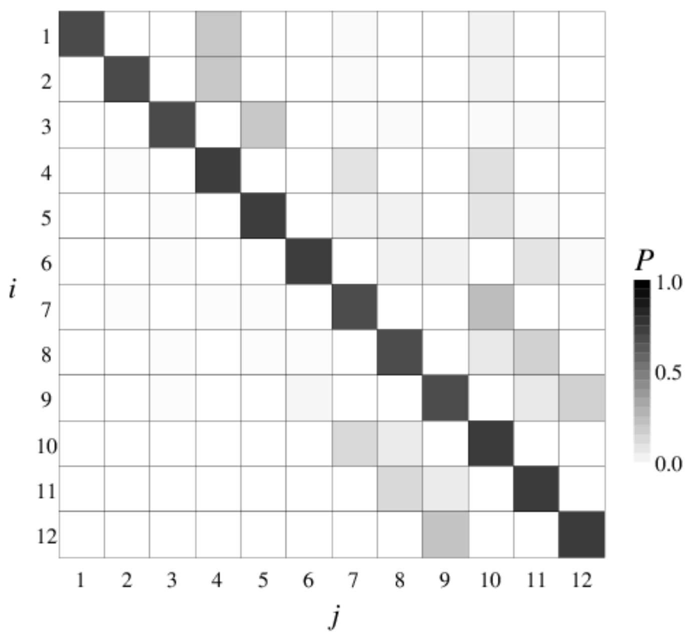

Figure 5-5 Storage_NO_3-N transition probability $P_{ij}(a_0)$ matrix after $\Delta t = 1$ week for Higashi irrigation pond due to decision $a_{0,}$ when operator do nothing.

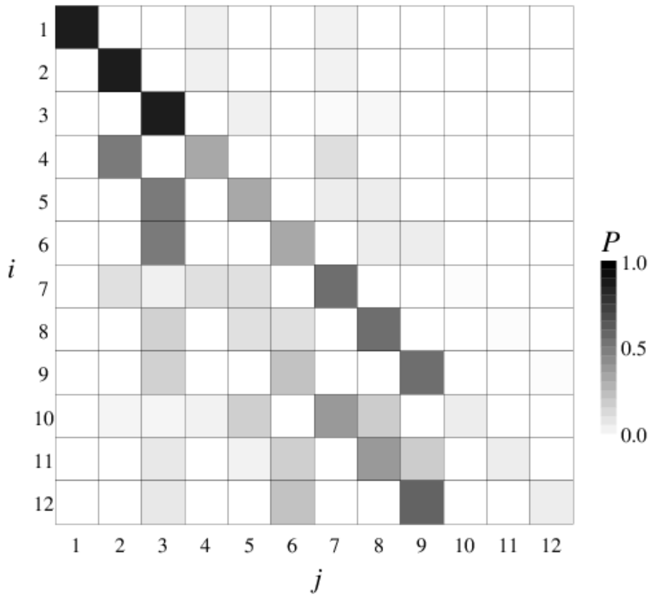

Figure 5-6 Storage_NO_3-N transition probability $P_{ij}(a_1)$ matrix after $\Delta t = 1$ week for Higashi irrigation pond due to decision $a_{0,}$ when irrigation water is released from the pond.

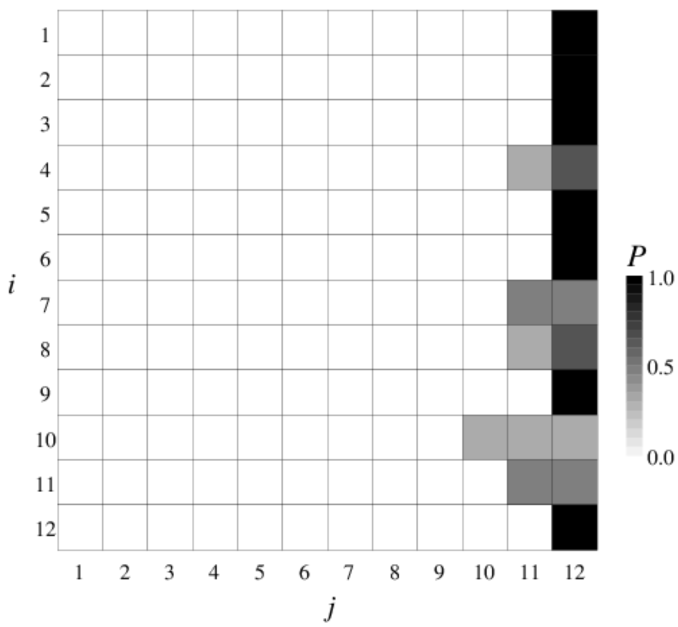

Figure 5-7 Storage_NO_3-N transition probability $P_{ij}(a_2)$ matrix after $\Delta t = 1$ week for Higashi irrigation pond due to decision $a_{2,}$ when water supplementation from Imago dam is introduced to Higashi irrigation pond.

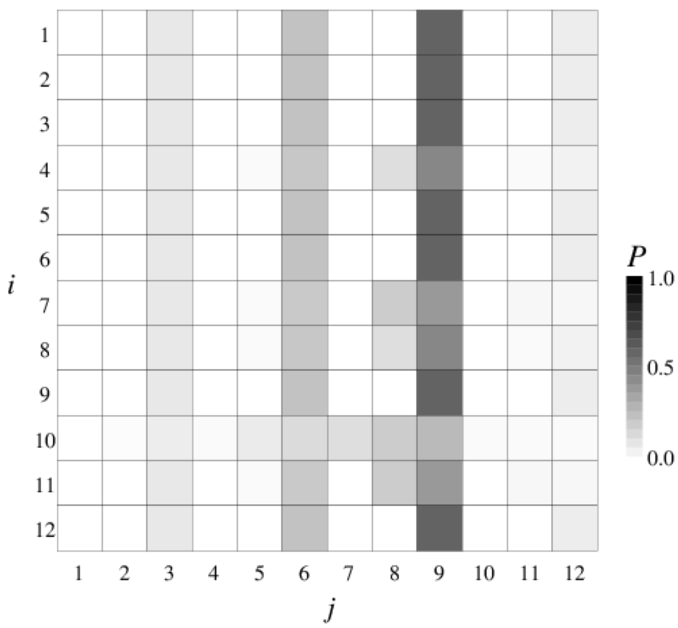

Figure 5-8 Storage_NO_3-N transition probability $P_{ij}(a_3)$ matrix after $\Delta t = 1$ week for Higashi pond due to decision a_3, when water is supplemented from Imago dam and later irrigate.

5.3.3.2 Optimal Reoperation Strategies for Higashi Irrigation Pond

Table 5-3 shows the resultant optimal costs $V^{\alpha}_{\Pi^*}(i)$ and the corresponding optimal reoperation policies Π^* obtained from computation of equations (19) and (20).

Table 5-3 Higashi irrigation pond optimal operation policies Π^*, and the corresponding optimal costs $V^{\alpha}_{\Pi^*}(i)$, for the pond $i \in X$ states.

	$i \in X$											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$V^{\alpha}_{\Pi^*}(i)$ (US$)	791	791	791	711	758	758	409	614	725	325	550	692
Π^*	a_3	a_3	a_3	a_3	a_3	a_3	a_1	a_1	a_3	a_1	a_1	a_1

The result shows that the optimal strategy to apply when Higashi irrigation pond is in $i \in X$ states 1-6 and 9 would be to introduce water supplements from Imago dam to Higashi irrigation pond, followed, by releasing irrigation water to the command area (a_3). For the remaining $i \in X$ states, 7-8, and 10-12, irrigation activity (a_1) alone would be optimally enough to sustain both production activities. Using the identified optimal control policies for the joint optimal operation of Higashi irrigation pond and Imago dam would significantly increase the water quantity and quality benefits of the Higashi irrigation pond, and accordingly facilitate a sustainable development of IIA in the area.

5. 4 Conclusions

The routine operation method of the Higashi irrigation pond for paddy-rice irrigation purposes is characterised with excessive water drawdowns, which sometimes leaves the pond near dry storage state. The successive antecedent critical low water levels, especially in the irrigation seasons, are linked to loss of aquatic ecosystem function of the pond. The Imago dam identified for water supplementing purposes of Higashi irrigation pond has water quality problems of high nitrate pollutant loads that could limit restoration of aquatic ecosystem function, particularly continued progression of fish populations. The Markov decision process (MDP) was formulated and applied to find the joint optimal operation policies for water storage and NO_3-N management in the Higashi irrigation that promote sustainable development of the integrated irrigation-aquaculture (IIA) therein. Regardless of the NO_3-N level, when the storage level of the Higashi irrigation pond is less than 2000 m^3 and at storage level 2000-3000 m^3 when the NO_3-N level is above 3 mg/L, the optimal policy is to introduce water supplements from Imago dam until its full capacity, and then followed by the irrigation activity. For all other pond states above the pond storage level of 2000 m^3 despite the NO_3-N level, the irrigation activity alone would be optimally enough. The reoperation of the irrigation ponds in the paddy irrigation schemes for IIA development using the above-formulated MDP method could increase the profitability of the smallholder farmers, through recovery of fish ecosystems in the ponds and preservation of the existing irrigation benefits, with no jeopardizing of the paddy environment multifunctionality. The method can also be readily adapted to other agricultural watersheds, which have other water quantity and/or quality problems. However, the implementation requires a careful analysis and in-depth evaluation of different hydrologic periods to produce model simulations that fully describe water quality and quantity changes in the respective study ponds.

CHAPTER 6 Summary and Conclusions

6.1 Summary

This thesis addressed water environment problems in the intensive agricultural areas, focusing in particular on the green tea and paddy rice crops dominated agricultural watersheds of Japan. The study was carried out in Imago area extends over the Nunobiki hills and adjacent valleys of Shiga Prefecture, Japan (34 96 N and 136 21 E).

The periodic water quality monitoring results from year 2013 to 2015 in the Imago area show that nitrate pollutant loads of agricultural drainage water from the green tea plantations were continuously sufficiently high enough to cause water pollution to irrigation dams and to Yama River via the drainage channels. This was despite the concerted efforts by farmers in Imago area to reduce amounts of nitrogen fertilizer applied to tea fields. Further nitrogen fertilizer reductions to tea crop beyond the recommended are discouraged because they might lead to reduced tea yields and quality. Unfortunately, the observed nitrate-nitrogen levels of agricultural drainage water from the green tea plantations to the Yama River were high enough to pollute the river. In addition, the irrigation dams, which include green tea plantation land-uses as runoff catchment areas, show that they were being nitrate-nitrogen polluted by agricultural runoffs from the upland green tea plantations. In addition, one of the irrigation ponds called Higashi shows that it has a history of temporary water shortages. Every successive year it is associated with excessive irrigation water drawdowns, and in some cases, the irrigation water is withdrawn until near empty storage states. As a result, the assessed commercial aquatic value of the pond from 2013 to 2015 was almost negligible.

The decision support systems for the water environment management in such typical rural areas as Imago area under hydrological and socio-economic uncertainties were developed and applied to Imago area. The developed decision support systems in this thesis can be summarized as follows.

1) A robust optimal model for diversion of agro-fertilizing nutrient polluted agricultural drainage water from intensive agricultural systems to paddy fields was presented. Active

and abandoned paddy fields were hypothesized that they could act as nitrogen sinks to incoming nitrate-nitrogen concentrated drainage water from intensive agricultural systems, given the inherent dominant denitrification characteristic of paddies. Field tests were conducted where nitrate concentrated drainage water from green tea plantations was deliberately diverted into active and abandoned paddy fields. Significant temporal and spatial nitrate reductions were respectively observed in both paddy field types. With this recognition, a robust optimal policy model was developed to support the decision-making process for diversion of nitrate contaminated drainage water to paddy fields. The goal was to find the optimal fractions of the unit discharge to be diverted to paddy fields, which optimally maximizes the reduction of the nitrate-nitrogen entering into and polluting the adjacent river, and optimally minimizes further possible environment risks like nitrate leaching in the paddy fields. The application of the model to Imago area shows that diversions to paddy fields are optimally maximized to reduce nitrate pollution to the Yama River, averting environment risk of possible malfunctioning denitrification processes in the respective paddy fields. (Chapter 3).

2) A robust optimal model for sustainable joint production of green tea and paddy rice was presented. Nitrate concentrated drainage waters diverted into irrigated paddy fields with a standing crop rice, were hypothesized that they would avail nitrogen nutrients for plant uptake, since nitrogen is the most limiting nutrient for rice production. From the conducted field experiments where nitrate concentrated drainage water from green tea plantations was flowing into paddy rice fields with an established crop, significant nitrate reductions were observed during the rice growing season than during the non-rice growing season when the paddy fields had no standing crop. Using the robust optimal model as a decision support system, the application showed that diversions of nitrate concentrated drainage water to irrigated paddy fields could be increased from 42%-46% in non-rice growing season to 74%-84% in rice growing seasons. This points out to a potential of converting nitrogen polluted drainage water from green tea plantations into an economical value, where rice crops will have optimal access to substantial amounts of nitrogen nutrients and water

therein. Resultantly, this would translate into improved economic viability of paddy rice production with greater protection of the water environment from agrochemical pollution. (Chapter 3).

3) A stochastic model for optimal control of agrochemical pollutant loads from intensive agricultural systems into reservoirs for irrigation was presented. The reservoirs for irrigation, like paddy fields, were hypothesized that they could be operated to influence the downstream riverine transport of nitrate nutrients, since they are well positioned to intercept substantial amounts of fertiliser runoffs from upslope green tea plantations. A comparative field survey of the water quality attributes between reservoirs with only forest runoff catchment area and with both forest and green tea plantation land-uses was carried out over a period of two years. The results showed that reservoirs with runoff catchment areas of both forest and green tea plantations, including Imago reservoir, were significantly intercepting nitrate-nitrogen polluted runoffs that could be otherwise delivered to the adjacent river. To optimize the pollutant buffering function with a minimum risk of negatively altering the aquatic ecosystems supported by such reservoirs, a Markov decision process (MDP) model was developed. The application of the MDP model to Imago reservoir shows that the model facilitates optimal control of nitrate-nitrogen pollutant loads within the allowable limits and maintains the reservoir storage above the fixed environmental threshold while satisfying the irrigation water demand of the command area. (Chapter 4).

4) An optimal reoperation model for irrigation ponds for improving water environment productivity in paddy environments was presented. With an aid of an optimal reservoir operation model, the research explored how environment water productivity could be increased to improve the overall agricultural productivity of the paddy-rice environment, like Imago area, under constraints of spatial and temporal water shortages and agrochemical pollution of the irrigation ponds. The potential of upgrading the Japanese paddy-rice irrigation systems into integrated irrigation-aquaculture systems, as a way to

improve the overall productivity was examined. Since aquaculture depends on particular reservoir water quantities and water qualities, temporal water shortages and nitrate pollution of the irrigation ponds were taken as the major constraints to a successful integrated irrigation-aquaculture (IIA) production. An optimal reservoir reoperation model was formulated where the supposed IIA ponds were to be operated using water quality and quantity norms. The application of the model to the Higashi irrigation pond in the Imago area showed that the model can comprehensively deduce optimal discharge rates and timings for release of inflows and outflows aimed at preservation of irrigation and aquatic values of the pond. (Chapter 5).

6.2 Future Perspectives

This thesis developed decision support systems for water environment management in the rural areas under hydrological and socio-economic uncertainties. However, there still a need to develop enablers that motivate adoptions of the developed decision support systems in the rural areas. The following issues remain to be addressed in future researches.

- Formulation of a simple, practical compensation scheme and optimal incentive policy that boost farmers' adoption and use of nitrogen concentrated green tea drainage water in the paddy rice production.

- Identification of suitable amenable infrastructure, and respective optimal hydraulic designs, that facilitate optimal reduction and control of nitrogen pollution to the surface water bodies at minimum disturbance of agroecosystems.

- Finding the optimal mix of nitrate polluted agricultural tea drainage water and chemical nitrogen fertilisers for paddy rice production, which maximally reduce the amount of chemical nitrogen fertiliser-use at maximum minimum loss of potential rice yield and at maximum minimum risk of nitrate leaching.

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