Optimizing Water Management in System of Rice Intensification Paddy Fields by Field Monitoring Technology

(フィールドモニタリング技術による SRI 水田の最適水管理に関する研究)

CHUSNUL ARIF

クスヌル　アリフ

Department of Global Agricultural Sciences
Graduate School of Agricultural and Life Sciences
The University of Tokyo

Year of entrance for Doctor of Philosophy: 2010

Supervisor:

Masaru Mizoguchi (Professor)

Optimizing Water Management in System of Rice Intensification Paddy Fields by Field Monitoring Technology

(フィールドモニタリング技術による SRI 水田の最適水管理に関する研究)

Summary

Water consumption and greenhouse gas emissions have emerged as major issues in rice production. Conventional rice farming with application of continuous flooding is not essential to achieve good yield and is known as a major source of greenhouse gas emissions from paddy fields. Hence, system of rice intensification (SRI) is proposed as an alternative of rice farming with more efficient water use for producing more rice and reducing greenhouse gas emissions. The main challenge in the application of SRI is finding the optimal water management to raise yield and water productivity and to reduce greenhouse gas emissions simultaneously. To support this purpose, improving the technology for collecting precise field data is important through continuous measurements of related variables by a field monitoring system (FMS). Therefore, this study was conducted to achieve this purpose based on the FMS data.

Nine chapters were presented in this study. In chapter 1, the introduction presented the originality and the main objectives of this study. The main objectives were to develop and evaluate the FMS for SRI paddy field with different irrigation regimes, to identify effects of irrigation regime on yield and water productivity and greenhouse gas emissions, and then to find the optimal irrigation regime for maximizing yield and water productivity and reducing greenhouse gas emissions.

In chapter 2, a method of data acquisition was presented. Here, we used the FMS consisting of a FieldRouter equipped with a surveillance camera and connected to meteorological and soil data loggers. The meteorological data consisted of solar radiation, air temperature, relative humidity, wind speed, and precipitation, while soil data consisted of soil moisture and soil temperature. The FieldRouter was set to automatically work from 12:00 to 12:30 PM (local time) regulated by a timer to collect the data, and then to send the data as well as a plant image to the data server through the GSM connection. The FMS was installed in Nusantara Organic SRI Center (NOSC), Nagrak, Sukabumi, West Java, Indonesia. Four SRI paddy plots under different irrigation regimes were monitored by the FMS. The FMS was demonstrated to be effective, efficient and reliable in monitoring the plots during 2010-2012. The actual field conditions were monitored well in terms of image, numeric and graphic data. The data were then used for further analyses to find the optimal SRI water management.

In chapter 3, neural network (NN) models were proposed to estimate soil moisture based on meteorological data. Sometimes during the above monitoring period, some soil moisture data were lost by unexpected problems in the field, where the sensor was broken, the cable was unplugged or the data logger battery was depleted. Therefore, the motivation of this chapter was to solve the problems. We developed two NN models; the first model was developed to estimate reference evapotranspiration (ETo) according to maximum, average, and minimum values of air temperature and solar radiation; the second model was to estimate soil moisture according to the estimated ETo and precipitation. As the results of NN performance, ETo was accurately estimated by the first NN model with R^2 values

of 0.95 and 0.92 ($p<0.01$) and mean squared deviation (MSD) of 0.02 and 0.24 mm for training and validation processes, respectively. Then, the second model estimated soil moisture with R^2 values of greater than 0.70 ($p<0.01$) and MSD of lower than $3x10^{-4}$ cm^3/cm^3 for the processes. Thus, the tight correlations between observed and estimated values of soil moisture were generated by the models.

Water balance variables such as irrigation water, runoff, percolation and crop evapotranspiration (ETc) are required to evaluate effects of irrigation regime on yield and water productivity. However, the variables were not easily measured in the fields. In chapter 4, a linear program with Excel Solver method was proposed to estimate the variables based on the monitored and estimated data in chapters 2 and 3. When indirect validation was used, the method was reliable as indicated by R^2 values of greater than 0.90 ($p<0.01$) between observed and calculated values of soil moisture. As supporting evidences of the model reliability, a significant linear correlation of $R^2>0.97$ ($p<0.01$) was recognized between precipitation and estimated runoff. Also, a well-matching relationship between the total inflow and outflow was observed for all irrigation regimes.

In chapter 5, we used the estimated ETc in chapter 4 to determine crop coefficient (Kc) values for the SRI paddy. Usually, Kc value is estimated by using the lysimeter method. But the method is time consuming and expensive for equipment preparation. Therefore, we proposed a simple method using a linear program with Excel Solver to estimate ETc, and then the estimated ETc was used to determine Kc value. Here, we evaluated the method by comparing the estimated ETc and the ETc derived from the FAO procedure. The result showed that the estimated ETc had a highly significant correlation to the ETc derived from the FAO procedure. Then, the Kc value was well determined using the estimated ETc. The Kc gradually increased in the initial and crop development stages, and it reached a peak in the mid-season stage. Then, the Kc declined rapidly in the late season stage. The Kc trend agreed with the typical Kc trend described by the FAO procedure for most crops.

In chapter 6, water management in SRI was optimized by a genetic algorithm (GA) model to maximize yield and water productivity based on the monitored and estimated data in chapters 2, 3, and 4. Before performing optimization, a formula to describe yield by plant growth parameters was identified using multiple linear regression analysis. Then, the plant growth parameters were estimated by the NN model using the soil moisture data set. The results showed that plant growth and yield were clearly affected by irrigation regime. Then, according to the identification results, the optimal irrigation regime was represented by the optimal combination of soil moisture levels for the growth stages. The GA model recommended the optimal combination of soil moisture levels of 0.622, 0.563, 0.522, and 0.350 cm^3/cm^3 for the initial, crop development, mid-season, and late season growth stages, respectively. By this scenario, it was estimated that the yield can be increased up to 6.33% and water productivity up to 25.09% with water saving up to 12.71%.

In chapter 7, since the FMS was not yet equipped with greenhouse gas sensors and their data loggers, experiments to investigate effects of irrigation regime on greenhouse gas emissions were carried out separately in the greenhouse of Meiji University in Kanagawa Prefecture, Japan. There were two experiments, i.e., using lysimeters and pots with three different regimes and two replications in each experiment. We called the regimes as continuous flooding, combination, and intermittent drainage regimes for the lysimeter experiment, while wet, medium, and dry regimes for the pot experiment. As the results of both experiments, greenhouse gas emissions were clearly affected by water management. The combination regime was found to be the best strategy for mitigation of greenhouse gas emissions achieving a greater rice yield than the others, with water saving up to 16.92%. Meanwhile, in the pot experiment, the dry regime was the best for the mitigation, but this regime resulted in a lower yield than the wet regime.

All of the findings of this study were discussed in chapter 8. By adopting quasi-real time monitoring, the developed FMS was more power saving and Internet cost effective than real time monitoring. The field data were collected properly and could be used to find the optimal SRI water management. The proposed methods were reliable as indicated by their acceptable performances. The optimal SRI water management was the combination of soil moisture levels of wet, wet, medium, and dry for the initial, crop development, mid-season and late season stages, respectively. We called this regime as W-W-M-D regime. In the initial and crop development stages, the field should be kept at the wet level because the plants need enough water to meet their requirements for optimally developing root, stem, leaf and tiller. Meanwhile, in the mid-season stage the field should be drained to make the field in the medium level when plants are focusing on their reproductive period to avoid spikelet sterility. The medium level in the mid-season stage was also supposed to be an affective option to reduce greenhouse gas emissions from paddy field. This argument was supported by the result of lysimeter experiment (chapter 7) in which combination regime with the application of mid-season drainage produced the highest yield and water productivity and contributed lowest emission among the regimes. The lowest emission was caused by reducing methane emission significantly when the water was drained in the mid-season stage. Finally, in the last season stage, the field should be drained to make the soil in the dry level to save water because all plant organs have perfectly developed.

Finally, in chapter 9, we drew conclusions from the results described in the previous chapters. Based on the field experiments, the FMS was effective, efficient and reliable in monitoring SRI paddy field in Indonesia in long-term experiments. We found that the optimal SRI water management was W-W-M-D regime in maximizing yield and water productivity and supposed releasing the lowest amount of emission. For further studies, the utilization of FMS for SRI paddy fields may be enforced with greenhouse gas sensors and their data loggers. Then, the optimal water management can be determined not only for maximizing yield and water productivity but also for reducing greenhouse gas emissions.

Acknowledgments

First of all, Alhamdulillah, thanks to Allah SWT for the mercy and guidance in giving me full strength to complete my PhD thesis with the title “Optimizing Water Management of System of Rice Intensification Paddy Fields by Field Monitoring Technology”. Secondly, my deepest thanks to my supervisors, Prof. Masaru Mizoguchi, Prof. Budi Indra Setiawan and Dr. Ryochi Doi, for their full support and guidance to fulfill my study at Department of Global Agricultural Sciences, the University of Tokyo. I appreciate their great efforts spending the time to discuss, give advice and attention to my research and study. By their support, I feel happy and comfortable studying at the laboratory of International Agro-Informatics. Also, I would like to thank the rest of my thesis committee, Prof. Kazuhiko Kobayashi, Prof, Kensuke Okada, Prof. Seishi Ninomiya and Prof. Tetsuya Araki, for their encouragement, insightful comments, and constructive suggestions.

I owe a great many thanks to a great many people in the laboratory, Niwa-san, Tetsu-san, Kobayashi-san, Mallika-san, Hana-chan, K-chan, Ishiwata-san, Mitsuishi-san, and Akazawa-san who helped and supported me during the study there. A great many thanks also for Prof. Kosuke Noborio, Kudo-san, Shimoozono-san and Kurihara-san, a Professor and students of Meiji University who welcomed and helped me to conduct the experiments in their University. The experience of conducting the research there will never be forgotten. Also, special thanks to my Indonesian friends in the PPI Todai and Todaimuslim communities for their support and sharing many nice things during my stay in Tokyo making me feel at home.

I would also thank my institution, Department of Civil and Environmental Engineering, Bogor Agricultural University, for the permission and great cooperation and the support for my study at the University of Tokyo. I am grateful to the Directorate of Higher Education, Ministry of National Education, Republic of Indonesia for the generous financial support for my study through Dikti scholarship and supporting my research through the grant of International Research Collaboration and Scientific Publication. Also I am grateful to the

MEXT in Japan for their partial support through the GRENE (Green Network of Excellence) project.

Then, I would like to thank to my parents, my lovely wife (Asti Budi Utami) and all my lovely children (Nabilah-chan, Nawwaf-kun and Kinjiro-kun) for supporting me mentally and physically not just during these tasks but also during my whole study period and in all aspects of life.

Thank you very much all of you. I will never forget all of your kindness.

Sincerely yours,

Chusnul Arif

Table of Contents

List of Tables

List of Figures

Acronyms and abbreviations

SRI	System of Rice Intensification
AWDI	Alternate Wetting and Drying Irrigation
GWP	Global Warming Potential
FMS	Field Monitoring System
FS	Field Server
NN	Neural Network
GA	Genetic Algorithm
DAT	Days after transplanting
VWC	Volumetric Water Content
Kc	Crop coefficient
ETc	Crop evapotranspiration
ETo	Reference evapotranspiration
FAO	Food Agriculture Organization
MSD	Mean Squared Deviation

Chapter 1: Introduction

1.1 Background

Recently, the scarcity of water resources and competition for their use have made water saving the main challenge in maintaining the sustainability of rice farming. Therefore, water saving technology became one of the priorities in rice research (Barker et al. 2000). From previous findings, rice is highly possible to be produced under water saving regimes of system of rice intensification (SRI) in which continuous flooding irrigation is no longer essential to gain high yields and biomass production (Zhao et al. 2011; Sato et al. 2011; Lin et al. 2011).

SRI is well-known as a set of crop management practices for raising the productivity of rice by changing the management of plants, soil, water, and nutrients. Although some critics were dismissed to SRI (Sinclair and Cassman 2004; Sheehy et al. 2004; Dobermann 2004), its benefits have been validated in 42 countries of Asia, Africa and Latin America (Uphoff et al. 2011). In SRI paddy fields, intermittent irrigation is applied in which the field is allowed to dry during particular time instead of keeping them continuously flooding, a practice called alternate wetting and drying irrigation (AWDI) (Van der Hoek et al. 2001).

Many experiments have been conducted by comparing continuous flooding and AWDI regimes under SRI (Choi et al. 2012; Zhao et al. 2011; Sato et al. 2011; Hameed et al. 2011; Barison and Uphoff 2011; Chapagain and Yamaji 2010). Significant savings in water use can be achieved, as reported in studies that provide data for different countries, e.g., 28% in Japan (Chapagain and Yamaji 2010), 40% in Eastern Indonesia (Sato et al. 2011), and 38.5% in Iraq (Hameed et al. 2011). Also by SRI, the land productivity raised more than double in Madagascar (Barison and Uphoff 2011), 78% in Eastern Indonesia (Sato et al. 2011), 65% in Afghanistan (Thomas and Ramzi 2011), 42% in Iraq (Hameed et al. 2011), and 11.3% in China (Lin et al. 2011).

AWDI is also known as a mitigation strategy for greenhouse gas emissions such as methane and nitrous oxide from paddy fields (Li et al. 2011; Tyagi et al. 2010; Husin et al. 1995; Nugroho et al. 1994). Greenhouse gas emissions have attracted considerable attention because of their contribution to global warming which is represented by global warming potential (GWP). Comparing to continuous flooding of paddy field, AWDI regimes can reduce greenhouse gas emissions up to 37% from paddy soil in Japan and Indonesia (Hadi et al. 2010).

Therefore, water management plays important roles in SRI paddy fields to raise yield with less water input and reduce greenhouse gas emissions. Hence, it is important to find the optimal irrigation regime during cultivation period. However, there is a lack of information on effects of AWDI with different regimes on yield and water productivity as well as greenhouse gas emissions from SRI paddy fields. Thus, the current study was undertaken to investigate effects of different AWDI regimes on yield, water productivity and greenhouse gas emissions simultaneously. Then, the optimal irrigation regime during cultivation period was determined to maximize yield and water productivity and to reduce greenhouse gas emissions.

In order to support this study, improving in an information technology for collecting field data is important through the continuous measurements in which precise data such as soil and meteorological data can be collected from field monitoring. A demonstration study on field monitoring technology for SRI paddy field in Japan has been conducted (Manzano et al. 2011). However, the study was limited only to the demonstration of the functionality of the monitoring system for short-term experiments. Therefore, the current study proposed the developed of a field monitoring technology for long-term experiments with more effective power input and data connection by adopting quasi real-time monitoring.

1.2 Literature review

1.2.1 System of Rice Intensification

SRI was introduced firstly by Fr. Henri de Laulanié in the early 1980s in Madagascar. Recently, SRI became popular over the world by effort of Prof. Norman Uphoff from Cornell University. SRI is a set of crop management practices with six basic elements summarized by following points (Uphoff et al. 2011; Stoop et al. 2002):

1. Transplant young seedling while still at the 2–3 leaf stage, before the start of the 4th phyllochron of growth to retain most of the rice potential for roots and shoots growing (Nemoto et al. 1995).
2. Transplant quickly and carefully to avoid trauma to the roots within 15-30 minutes at a transplanted depth only 1-2 cm.
3. Single transplanting with wider spacing for better shoot and root growth according to soil quality.
4. Carefully controlled water management by avoiding continuous flooding.
5. Early and regular weeding as consequently of applying AWDI.
6. Apply compost to enhance soil organic matter as much as possible.

SRI represents an integrated and agro-ecological approach to irrigated rice allowing farmers to realize yields of up to 15 ton/ha with reduced irrigation water and mineral fertilizers' inputs demonstrated by participatory on-farm experiments conducted in Madagascar (Stoop et al. 2002). However, inverse results were obtained and concluded that SRI has no inherent advantage over the conventional system (Sheehy et al. 2004). Thus, it has been dismissed by vehement criticism and controversy like an ‘‘unidentified flying object’’ (UFO) or "unconfirmed field observation" (Sinclair and Cassman 2004).

The controversy of SRI motivates the researchers to investigate its elements including water management. Many studies have been conducted to investigate water saving regimes through AWDI under SRI in several countries (Choi et al. 2012; Zhao et al. 2011; Sato et al. 2011; Hameed et al. 2011; Barison and Uphoff 2011; Chapagain and Yamaji 2010). They reported that AWDI can save water input from 28% to 40% compared to continuous flooding irrigation and raise the yield up to 100%. The key is to keep soil moist enough to sustain plant growth, not too much water input by avoiding continuous flooding that the plants suffocate (Uphoff et al. 2011). However, any study on different irrigation regimes under non-flooding condition was not found yet. This study was important to find the optimal irrigation regime to raise yields with less water input as much as possible.

1.2.2 Greenhouse Gas Emissions from Paddy Fields

Global warming and climate change are hot topics of considerable scientific debate and public concern. GWP concept has been introduced to allow the comparison of the ability of each greenhouse gas emission to trap heat in the atmosphere relative to carbon dioxide (CO_2) over a specific time horizon. This is called the carbon dioxide equivalent (CO_2 eq) value and is calculated by multiplying the amount of gas by its associated GWP (Smith and Wigley 2000). Methane (CH_4) and nitrous oxide (N_2O) are two greenhouse gases contributing to GWP at 23 and 296 times greater than carbon dioxide, respectively (Snyder et al. 2007). Thus, these gases attracted considerable attention during the last decades because of their contribution to global warming (Neue et al. 1990; Bouwman 1990).

Paddy field is a major source of greenhouse gas emissions particularly methane (Setyanto et al. 2000; Cicerone et al. 1992). Although an early study found that nitrous oxide emission from paddy field to be negligible (Smith et al. 1982), however, recent study suggested that paddy field is important source not only methane but also nitrous oxide (Cai et al. 1997). Methane is produced by methanogens during organic matter decomposition, under an environment where the oxygen and sulfate are scare (Bouwman 1990; Cicerone and Oremland 1988) such as in flooded condition. Meanwhile, nitrous oxide is primarily produced from microbial processes, nitrification and denitrification in soil (Mosier et al. 1996).

A trade-off effect between methane and nitrous oxide is clearly observed (Cai et al. 1997). The nitrous oxide flux is very small when paddy field is flooded, but its flux reaches a peak at the beginning of the disappearance of flooding water. In addition, its flux rises dramatically when fertilizer N induced to the field (Snyder et al. 2007; Akiyama et al. 2005). In contrast, methane flux reaches a peak during flooding and is significantly reduced by water drainage (Setyanto et al. 2000). Therefore, water management is one of the most important factors in rice production and most promising option for methane and nitrous oxide mitigation (Tyagi et al. 2010; Akiyama et al. 2005).

Many researchers have been conducted the experiments to find the optimal water management for mitigating of greenhouse gas emissions from paddy fields. They found that mid-season drainage irrigation may be an effective option to reduce greenhouse gas emissions (Towprayoon et al. 2005; Akiyama et al. 2005). However, the experiments were conducted under conventional crop management. Therefore, further study is needed to find effective option for mitigating gas emissions from paddy fields particularly under SRI.

1.2.3 Field Monitoring Technology

Since 2007 the technology to collect real-time precise environmental data have been developed through ubiquitous field monitoring for agricultural production using field monitoring system involving the Field Server (FS), under the “Database-Model cooperation system” project of the Ministry of Agriculture, Forestry and Fisheries of Japan (Honda et al. 2008; NARO 2007). The FS is an automatic monitoring system consisting of a CPU as a web server, an analog-to-digital converter, an Ethernet controller; sensors to measure air temperature, relative humidity, solar radiation, soil moisture, soil temperature, and electrical conductivity; and a charge-coupled device camera. It can transfer high-resolution pictures of fields and sensing data through Wi-Fi broadband networks (NARO 2009).

However, there was problem limiting its stability. From the field experiences, the FS broke down after only half a year when the heat and ultraviolet light weakened their acrylic poles (Mizoguchi et al. 2009). The stability depends on the field solar power supply, the antenna, the local electrical power supply, and the Internet connection. If any of them has a problem, the data will be lost because the FS does not have any data logging function.

Therefore, the new generation of FMS is being developed by using FieldRouter since 2010 (Mizoguchi et al. 2011). A newly developed FMS is a hybrid remote monitoring system which consisted of FieldRouter (X-Ability Co. Ltd., Tokyo) and connected some data loggers. FieldRouter is different from the FS as presented in Table 1. FieldRouter has capability to send the daily data through Internet connection. It consists of 3G/GSM modem, mini PC, camera, battery and timer then all of those components are kept in a water proof and dust tight box. Detail components of FieldRouter and how to install it can be refered to the FieldRouter manual in Appendix 1.

Table 1. Comparison of FS and the FieldRouter (Mizoguchi et al. 2011)

No	Items	Field Server	FieldRouter
1	Monitoring	Real-time and continuous	Daily monitoring/ quasi real-time
2	Operation	All day	A half hour/day
3	Power	High power consumption by using big solar panel (100 W size: 1m x 2m	Lower power consumption by using 6 W solar panel
4	Internet line	Internet with static IP address	Mobile phone Internet (3G/GSM)
5	Internet cost	More expensive	Cheaper
6	Data logger	No data logger function, data are directly and continuously sent to the server	Any data loggers can be connected
7	Set up process	Difficult system set up: Phone setting, Internet modem setting, IP cam, WiFi AP and sensors	Easy set up: - Device name, mobile name company - Automatic data logger detection
8	Collecting data	Data lost when power or Internet fails	Data secured in each data logger. However, the data will be lost immediately if the sensor cable unplugged and the battery depleted.

The advantages of FieldRouter are small power source, easy set up, cost-effectiveness of Internet connection using mobile line, can check battery level from the remote laboratory, data loss can be minimized because the data are secured by the data loggers and stored in data center. The current study was conducted to utilize the FMS using FieldRouter for SRI paddy field in Indonesia. Then, the feasibility of the system was evaluated.

1.3 Objectives

The main objectives of the current study are:

a. to develop and evaluate a field monitoring system (FMS) for SRI paddy field in acquiring continuous field data

b. to investigate effects of different AWDI regimes on yield and water productivity based on the monitored data

c. to find the optimal irrigation regime for maximizing yield and water productivity

d. to investigate effects of irrigation regime on greenhouse gas emissions from SRI paddy field

e. to find the optimal irrigation regime for maximizing yield and water productivity and reducing greenhouse gas emissions from SRI paddy field simultaneously

1.4 Structure of thesis

Nine chapters were presented to realize the main objectives (Figure 1). In chapter 1, the introduction presented the originality and the main objectives of this research. Also, previous studies were cited to explain the present achievements related to the study. Then, chapter 2 presented the data collection from SRI paddy field in Indonesia through continuous measurements by the FMS. Evaluation of FMS was then also discussed in this chapter to realize the first main objective.

Sometimes, the monitored data such as soil moisture values were lost due to unexpected problems when the sensor was broken, the cable was unplugged or the data logger battery was depleted. Since soil moisture data are needed to evaluate effects of irrigation regime on yield and water productivity, the lost data were estimated by the neural network (NN) model to estimate soil moisture data by considering meteorological data in chapter 3.

For evaluating the regimes adopted in the current study on yield and water productivity, water balance variables such as crop evapotranspiration, percolation, irrigation water and runoff are needed. However, these data were not easily measured in the field. Thus, we presented a novel method to estimate non-measurable water balance variables using the monitored data in chapter 4. Then, daily crop coefficient (Kc) for SRI paddy was determined using estimated crop evapotranspiration in chapter 5. Kc value is important to study the plant response to available water in the field.

The monitored and estimated data were then used to determine an optimal irrigation regime for each growth stage using genetic algorithm (GA) model in chapter 6. Before running the model, effects of different irrigation regimes on yield and water productivity were identified by considering plant growth and environmental parameters. This chapter realized the second and third main objectives.

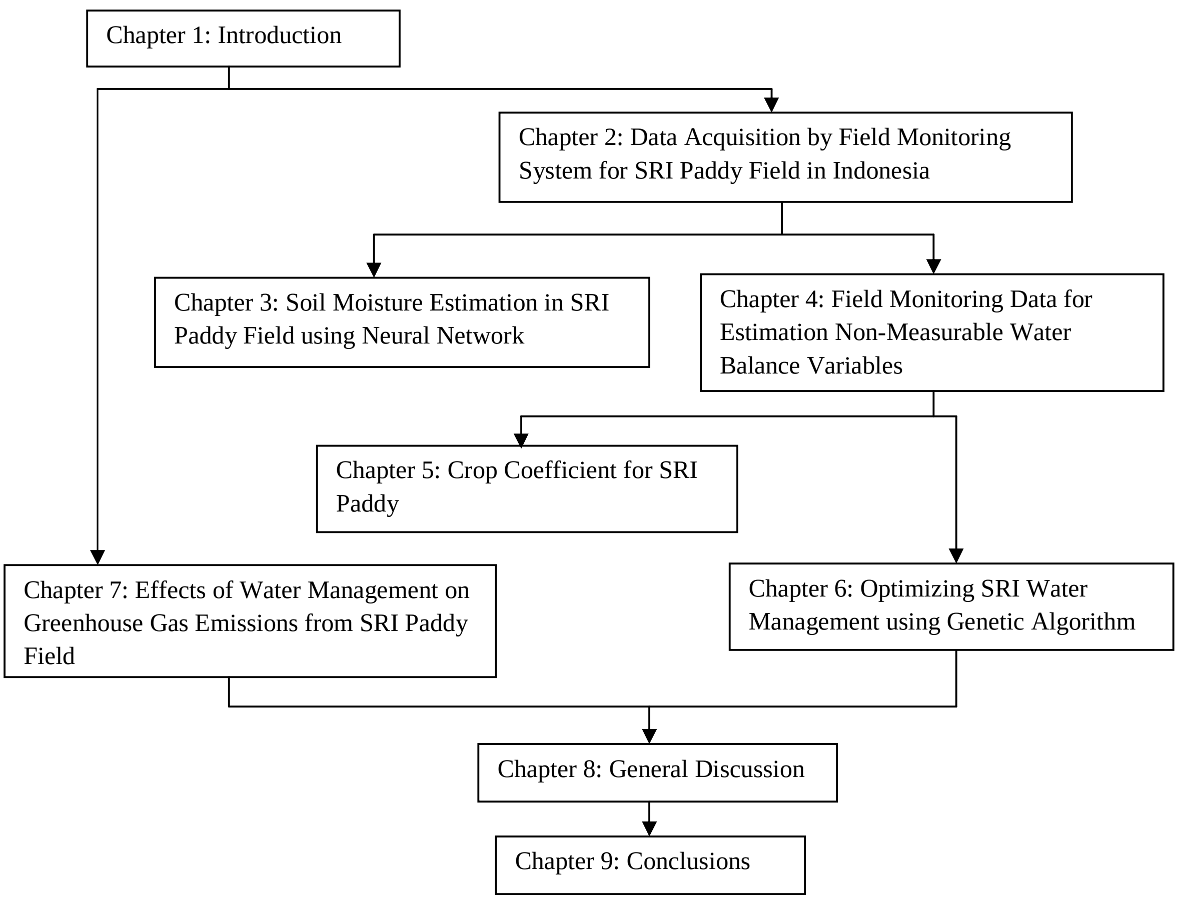


Figure 1. Structure of the current study

In chapter 7, since the FMS was not yet equipped with greenhouse gas sensors and their data loggers, experiments to investigate effects of irrigation regime on greenhouse gas emissions were carried out separately in the greenhouse of Meiji University in Kanagawa Prefecture, Japan. Field experiments consisted of three irrigation regimes with two replications in the lysimeter and the pot. Greenhouse gas emissions, consisting of methane and nitrous oxide, were measured manually and then, the values were used to determine GWP for each regime. This chapter was presented to realize the fourth main objectives.

In chapter 8, interconnection among chapters were discussed particularly the main finding of this study to realize fifth main objectives. Finally, in chapter 9, conclusions were drawn from all the results in realizing all of objectives. Also, we enlisted some points to be considered for further studies related to the current achievements.

Chapter 2: Data Acquisition by Field Monitoring System for SRI Paddy Field in Indonesia

2.1 Background

The challenges to raise rice productivity in Indonesia have been increasing due to the increased population and reduced arable area. On the other hand, the competition of water resource for rice production increased with the increased water requirement for paddy fields as affected by climate change (De Silva et al. 2007). Alternative rice cultivation with more efficient water input is needed for ensuring the sustainability of rice production. SRI is proposed as an alternative rice cultivation with more efficient water input by providing suitable growing conditions in the root zone. The basic concepts are single planting with younger seedlings (5–14 days after seeding), wider spacing between transplanted seedlings, application of intermittent irrigation, organic fertilizer and very active soil aeration (Uphoff et al. 2011; Stoop et al. 2002).

Since introduced in 1999 dry season by the Agency for Agricultural Research and Development in Indonesia, SRI has been widespread in some areas through several programs in Indonesia. By adopting AWDI regime, water use can be reduced up to 40% (Sato et al. 2011; Sato and Uphoff 2007). However, there were some limitations in disseminating SRI in Indonesia, such as determining optimal irrigation regime and developing irrigation water control (Gani et al. 2002).

Further investigation focusing to find optimal irrigation regime for raising yield and water productivity are urgent for SRI application in Indonesia. To support this study, data on rice field environment such as soil and meteorological data through continuous measurements are needed. The soil data, such as soil moisture, are important to identify water availability in the field. In SRI, soil moisture information is needed to recognize soil water status, whether in the wet or the dry condition. Then, irrigation water can be easily determined in particular time. Meanwhile, information on meteorological data such as precipitation, air temperature, relative humidity, solar radiation and wind speed are required to consider natural environmental effect in determining irrigation water.

Precipitation data are commonly used to determine starts of rainy and dry seasons, e.g., in Indonesia (Irsyad 2011), while the other meteorological data are the main factors to determine evapotranspiration (Allen et al. 1998). Therefore, the FMS is required to provide such data.

A study on the development of FMS for SRI paddy field was started since 2008 using the FS (Setiawan et al. 2010; Gardjito et al. 2008). However, the study was limited only for a short-term experiment and there were problems related to the stability of FS and data acquisition. The previous FMS with the FS was not connected to the meteorological sensors such as air temperature, humidity, solar radiation and wind speed. Therefore, this study was initiated for the development of FMS with FieldRouter for SRI paddy field to provide continuous soil and meteorological data in Indonesia.

The objectives of this chapter were to develop a FMS for SRI paddy field in Indonesia under different irrigation regimes, and then to evaluate the feasibility of the FMS for long-term experiments.

2.2 Methodology

2.2.1 Field Experiments

The FMS was set up under natural environment in the Nusantara Organic SRI Center (NOSC), Nagrak, Sukabumi, West Java, Indonesia located at 06º50’43” S and 106º48’20” E, at an altitude of 536 m above mean sea level (Figure 2) prior to three cropping seasons (Table 2).

Table 2. Cultivation period of each cropping season

Season	Planting date	Harvesting date	Rainy/Dry
First	14 October 2010	8 February 2011	Rainy
Second	20 August 2011	15 December 2011	Dry - Rainy
Third	22 March 2012	5 July 2012	Rainy - Dry

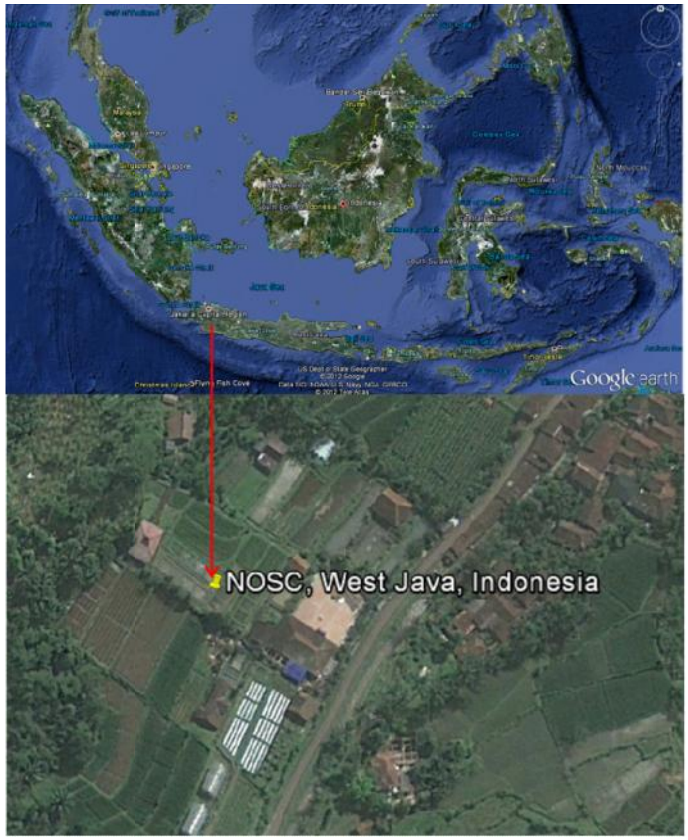


Figure 2. Experimental field location in NOSC, West Java, Indonesia

There were four plots and each plot was planted with the variety of rice (*Oryza sativa* L), Sintanur using the following SRI elements: single planting of young seedlings spaced at 30 cm × 30 cm (Figure 3), applying an organic fertilizer at 1 kg/m^2 in the land preparation, but no chemical fertilizer. The weeding was performed every 10 days in the period between 10 and 40 days after transplantation supplying local indigenous microorganisms to enhance biological activity in the soils (Uphoff et al. 2011).

(a) Young seedlings

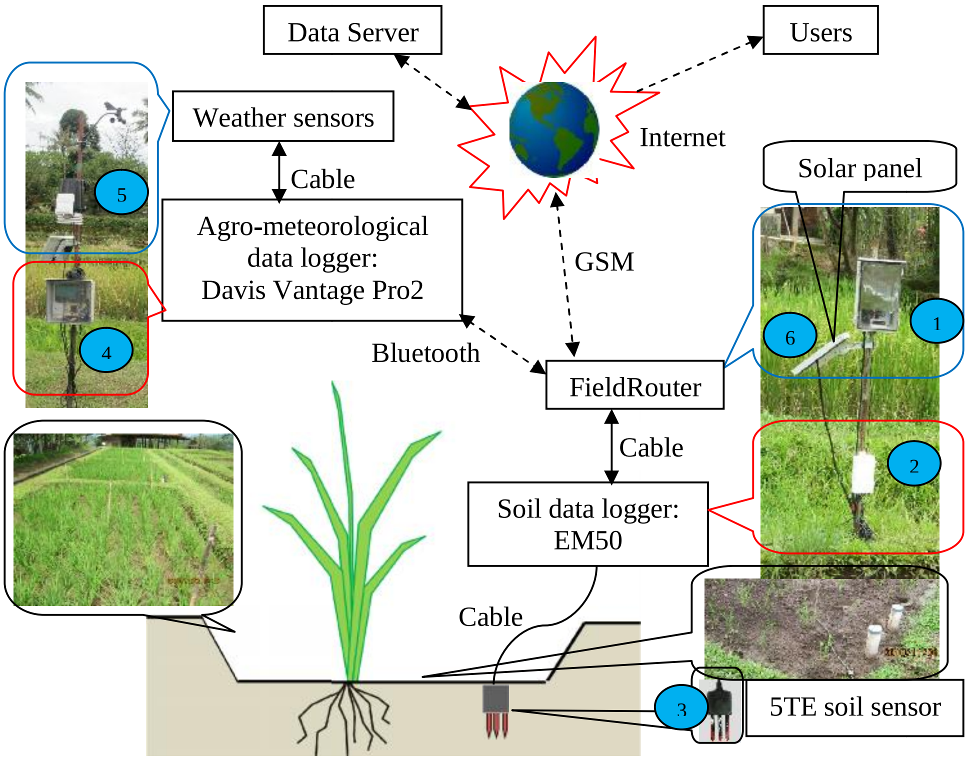
(b) Single transplanting

(c) Wider spacing

Figure 3. SRI elements of the current study

2.2.2 Field Monitoring System

We developed the FMS for SRI paddy field in Indonesia employing of a FieldRouter equipped with a surveillance camera and connected to meteorological and soil data loggers. Here, we used a Davis Vantage Pro2 Weather Station (Davis instruments Corp, California) consisting of Davis console (data logger) and weather sensors. The weather sensors consisted of solar radiation, air temperature, relative humidity, wind speed, and precipitation sensors. Meanwhile as the soil data logger, we used an Em50 data logger developed by Decagon Devices, Inc., USA. The Em50 was connected to four soil moisture and soil temperature sensors (5TE) installed at the 10 cm depths from the soil surface in each plot.



Note:

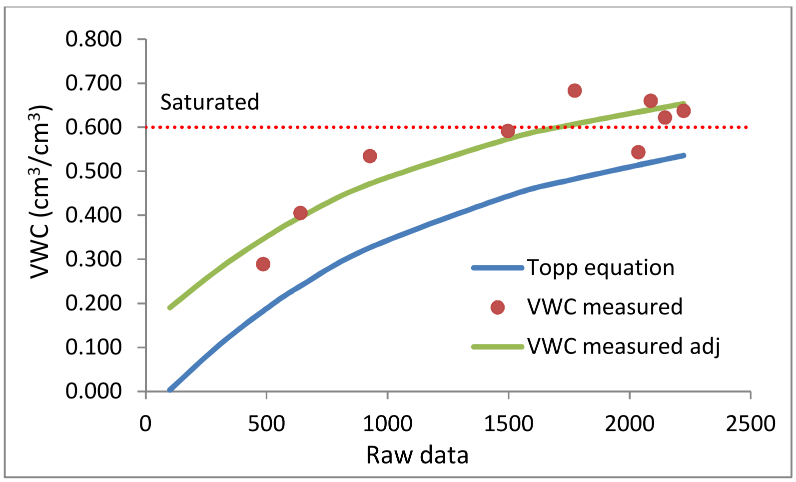
1. FieldRouter
2. Em50 Data logger
3. Soil moisture sensor (5TE)
4. Davis console
5. Weather sensors
6. Solar panel for FieldRouter

Figure 4. Connection of the FMS for SRI paddy field in Indonesia

Connection system of the current FMS is shown in Figure 4. The FieldRouter was connected to Davis console by using Bluetooth connection, and connected to the Em50 data logger by the cable. Every sensor was set up to measure soil and meteorological parameters every 30 minutes. Then, the data were stored in each data logger. The FieldRouter was set to automatically work from 12:00 to 12:30 PM (local time) regulated by a timer to collect the data from the both data loggers, and then to send the data as well as a plant image to the data server through the GSM connection. Users could easily obtain the data by accessing SRI observation website (http://x-ability.jp/FieldRouter/vbox0047/).

2.2.3 Calibration of soil moisture sensor

Custom calibration of soil moisture sensor (5TE) was conducted to improve the accuracy. 5TE sensor measures soil moisture (in the volumetric water content (VWC) of the soil) by measuring the dielectric constant of the soil, which is a function of water content. However, not all soils have identical electrical properties. Decagon Devices, Inc. use Topp's equation to convert from raw data to the VWC (Topp 1980). This equation results in approximately ±3-4% accuracy for most mineral soils. However, Decagon Devices, Inc. recommends the users to conduct custom calibration to improve the accuracy to ±1-2%.



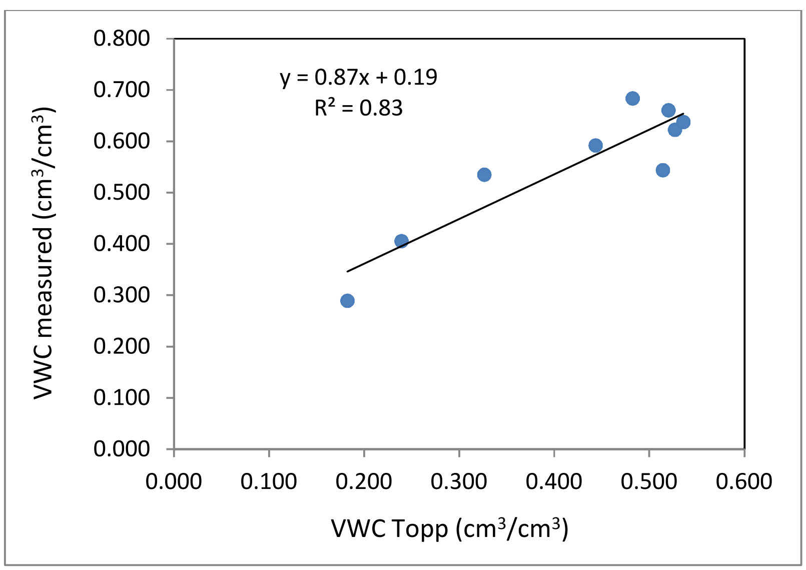


Figure 5. Calibration equation of 5TE soil moisture sensor

We used the standard calibration technique following the general procedure for calibrating capacitance sensors outlined (Starr and Paltineanu 2002). We collected approximately 4 liters of bulk soil and then air dried the soil by previously removing large objects. The result of calibration is presented in Figure 5.

The red and blue solid circles show soil moisture determined in the laboratory. These values were different from those derived from Topp's equation but the trends were same. Therefore, we used a linear correlation between Topp's equation and measured soil moisture. We got the linear equation of $y = 0.87x + 0.19$ derived from Topp's equation to obtain measured soil moisture. From the calibration, it was also known that the sensitivity sensor increased when soil moisture closer to saturated conditions. The coefficient of determination (R^2) of 0.83 was obtained between Topp's equation and measured soil moisture.

2.2.4 Irrigation Regimes

Four experimental plots were irrigated under different irrigation regimes. The area of each plot was 4 x 4 m^2. Non-flooding conditions were applied in all regimes, and then in each growth stage, the water levels were planned to be 0 cm, -5 cm, -10 cm and -20 cm from 20 days after transplanting (DAT) until harvesting (Figure 6).

Note: A: 0 cm (control), B: -5 cm, C: -10 cm, D: -20 cm

Figure 6. Experimental plots of SRI paddy field

However, since actual water level could not be controlled well by the irrigation control system, the water level varied in each plot. Therefore, we classified the soil moisture levels into three, i.e., wet (W), medium (M) and dry (D) according to the soil retention curve as presented in Figure 7.

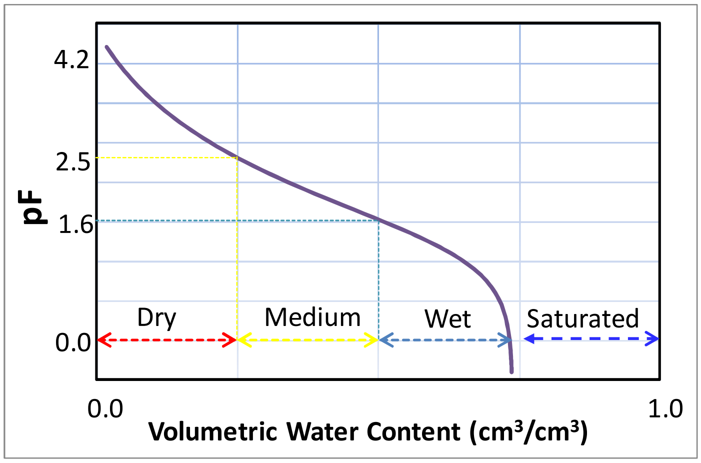


Figure 7. Classification of field moisture conditions during the cultivation period

Table 3. Soil properties of each experimental plot

Soil property	Experimental plots			
	Plot A	Plot B	Plot C	Plot D
Soil texture:				
Clay (%)	31	27	32	35
Silt (%)	66	68	64	59
Sand (%)	3	5	4	6
Texture name	Silty clay loam			
Saturated hydraulic conductivity (Ks, mm/d)	12.7	20.1	21.6	23.8
Field capacity (cm^3/cm^3)	0.443	0.437	0.445	0.430
Permanent wilting point (cm^3/cm^3)	0.306	0.307	0.331	0.307
Effective soil depth (Zr, mm)	300	300	300	300

The texture of the soil of the experimental plots was silty clay loam with other properties summarized in Table 3. The wet level was achieved when the soil suction was between 0 (saturated) and 1.6 which was the air entry value for this soil. The medium level was achieved when the soil suction value was between 1.6 and 2.54 which was the field capacity value. When the soil was drier than the medium level, the level was dry (Figure 7). The experimental plots differed in the parameters of the curve described by the Van Genuchten model (Van Genuchten 1980).

The model expressed in equation 1 shows the relationship between soil moisture and pressure head.

$$\theta = \theta_r + \frac{(\theta_s - \theta_r)}{[1 + (\sim h)^n]^m} \qquad (1)$$

where, θ is soil moisture (cm^3/cm^3), h is pressure head (cm H_2O), θ_s, θ_r, α, n, and m are Van Genuchten's independent parameters for saturated water content (cm^3/cm^3), residual water content (cm^3/cm^3), and shape factors (α, n and m), respectively. These parameters were estimated from observed soil-water retention data. The values of the parameters are presented in Table 4.

Table 4. Genuchten's parameters of each experimental plot

Parameters	Experimental plots			
	Plot A	Plot B	Plot C	Plot D
Saturated water content (cm^3/cm^3)	0.597	0.578	0.600	0.595
Residual water content (cm^3/cm^3)	0.250	0.250	0.300	0.260
Shape factor:				
α	63	63	63	50
n	1.330	1.316	1.410	1.340
m	0.248	0.240	0.291	0.254

Both soil properties and Genuchten's parameters were identical among the plots. From the laboratory analysis, soil textures represented by the composition of clay, silt and sand were also similar. Soil moisture at field capacity in the plots were around 0.440 cm^3/cm^3 and at permanent wilting points around 0.300 cm^3/cm^3 indicating the total available water was approximately 42 mm in the effective depth of 300 mm according to the FAO calculation (Allen et al. 1998).

2.3 Results

2.3.1 SRI information system website

The data can be accessed through integrated FMS, http://www.x-ability.jp/~swampred/index.php?dfw=fns2 developed by X-Ability, Ltd (Mizoguchi et al. 2011). The data can be accessed by clicking the image, and then it is linked to a specific location. In addition, there are "I", "M", and "S" letters representing the acquisition status of image, meteorological and soil data, respectively (Figure 8). The status of today is shown in the right side and the previous day left side of the picture. If all letters appear for a specific day, it means that the FieldRouter could send all data during that day.

Figure 8. The website for SRI paddy field in NOSC, Indonesia

FMS for SRI paddy field in NOSC, Indonesia, the link is http://x-ability.jp/FieldRouter/vbox0047/. Here, we can access all meteorological and soil data as well as image data (Figure 9). In this website, the GPS link location is also available, so the users know the location of the FMS. The data are presented in the graphics of each meteorological and soil parameters and the raw data. The meteorological data can be identified by “Davis Vantage Pro2”, while soil data can be identified by “Em50NOSC”. The users can access the graphics data by clicking the symbol of graphic in the right side. Meanwhile, the raw data can be accessed by clicking the sign of raw data behind the sign of graphics data. After downloading the raw data, those data should be converted using ECH2O utility software from Decagon Inc website (http://www.decagon.com/). In addition, this website also presents the battery level of each data logger, so we can estimate the right time to go to the field to replace the battery.

Figure 9. Another website for SRI paddy field in NOSC, Indonesia

2.3.2 Plant growth monitoring

Daily plant image was sent by FieldRouter through GSM connection to the server. It was presented as a single image as shown in Figure 8. To see the overview of the plant images during the planting period, an image calendar was available (Figure 10). As an example in October 2010, there were 5 plant images failed being sent to the server due to GSM connection or battery depletion problem.

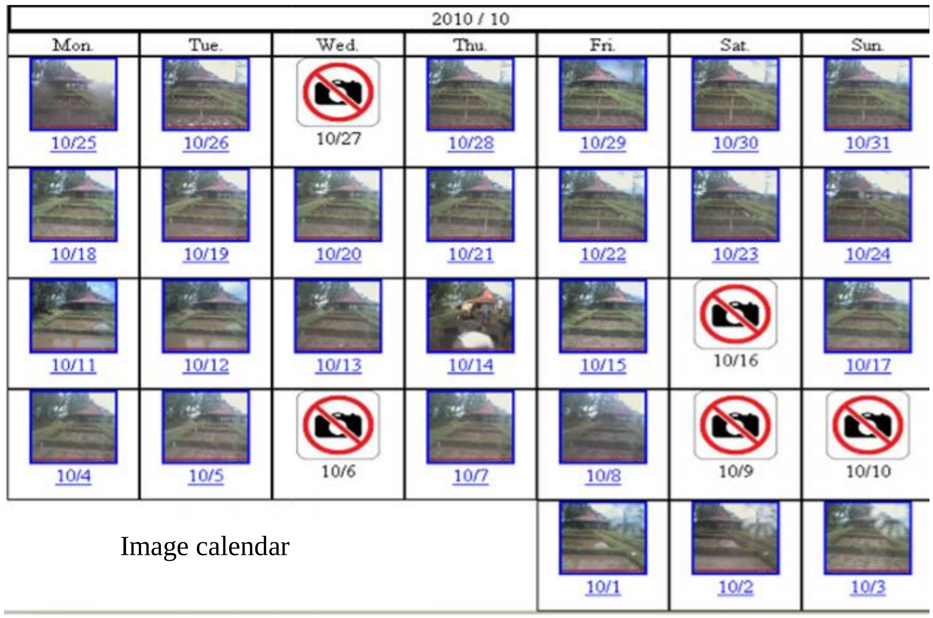


Figure 10. Calendar of field image data

Planting date　Early stage　Vegetative stage

Crop development　Mid-season stage　Late stage

Figure 11. Plant growth was monitored by the FMS

Plant images that represented each growing stage were captured and sent well to the server as presented in Figure 11. In the early stage, the plant was hardly visible and the field image was dominated by soil due to a single planting with very young seedling adopted by SRI. On the contrary, in the reproductive and late stages, the plants grew well to cover the entire field. It was probably indicated that a single plant per hill with very young seedling promote more dry matter production compared with the three plants per hill (San-oh et al. 2004).

2.3.3 Dynamic changes in Meteorological parameters

Daily monitoring data

Figure 12 shows the hourly changes in air temperature and relative humidity during 15-31 October 2010. The trend of air temperature was found to be contrasting to that of relative humidity. Maximum air temperature was observed everyday around 12:00 – 02:00 PM when its humidity was minimum. The maximum air temperature was almost 30^{o}C, when its humidity was around 60% as the minimum level on 16 October 2010 12:00 PM. Air temperature was affected by solar radiation so that the maximum temperature was observed when solar radiation was also at its maximum level as presented in Figure 13.

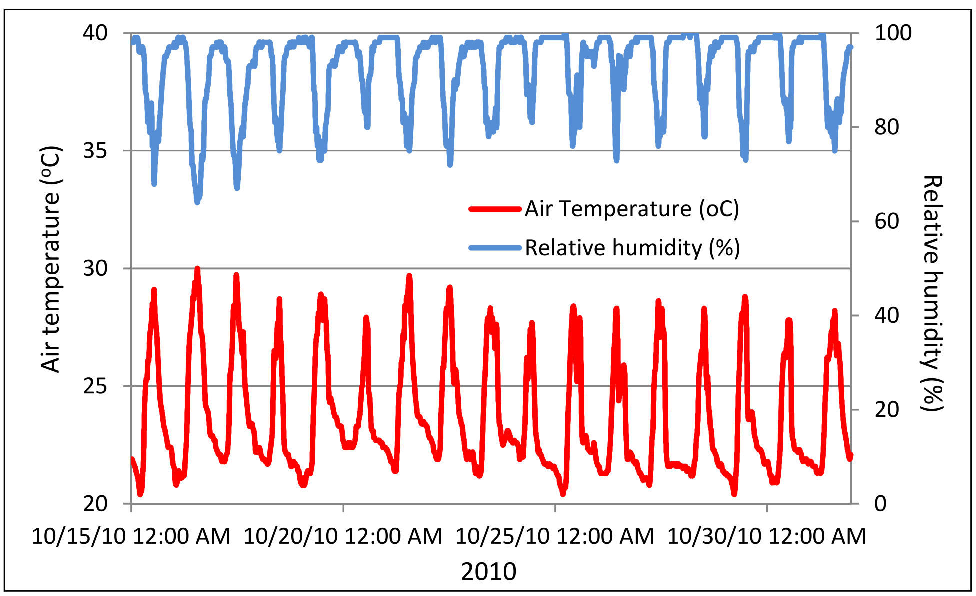


Figure 12. Hourly changes in air temperature and relative humidity

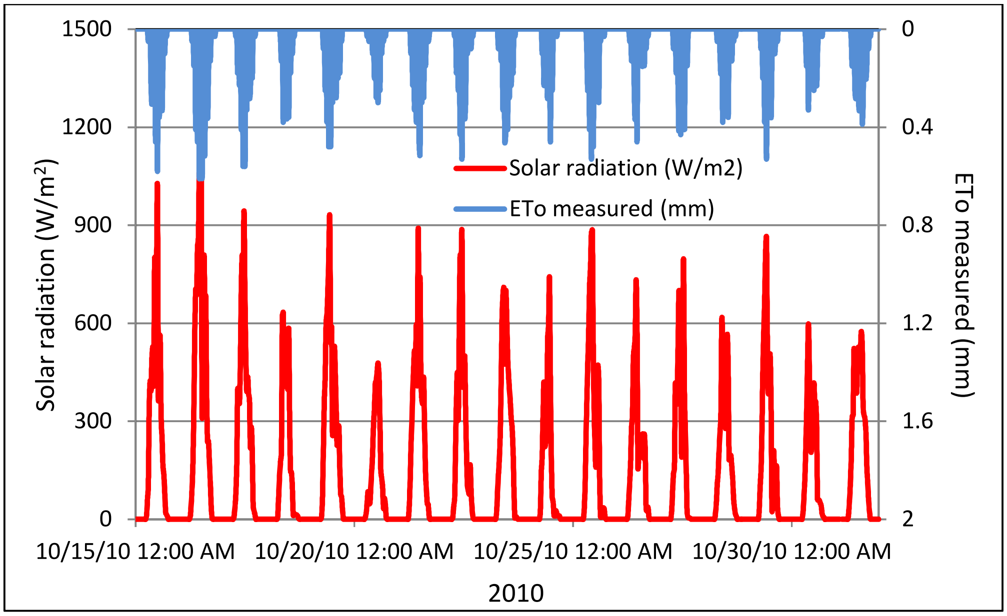


Figure 13. Hourly changes in solar radiation and measured reference evapotranspiration (ETo)

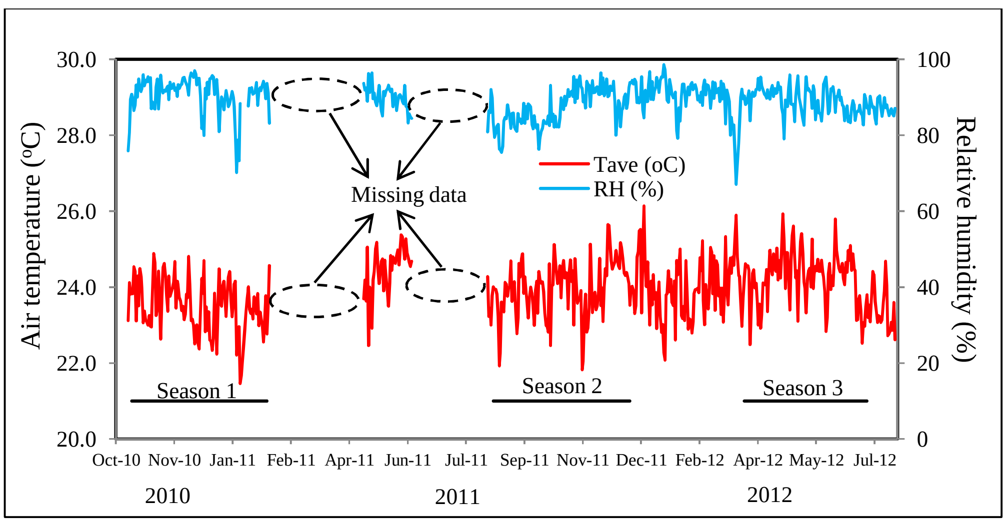


Figure 14. Daily average air temperature and relative humidity

Figure 13 shows hourly changes in solar radiation and measured reference evapotranspiration during 15-31 October 2010. Solar radiation had a positive correlation to the measured reference evapotranspiration (ETo). A maximum solar radiation was reached on the time around 12:00 – 02:00 PM as well as ETo. The result indicated that the water requirement for the plant reached the maximum level during that time.

From the hourly data, we calculated the daily data of each meteorological and soil parameter. During the middle February to April 2011 and July 2011, the meteorological data were lost when the battery of Davis console was depleted and the power back up from solar panel was not enough (Figure 14 and Figure 15).

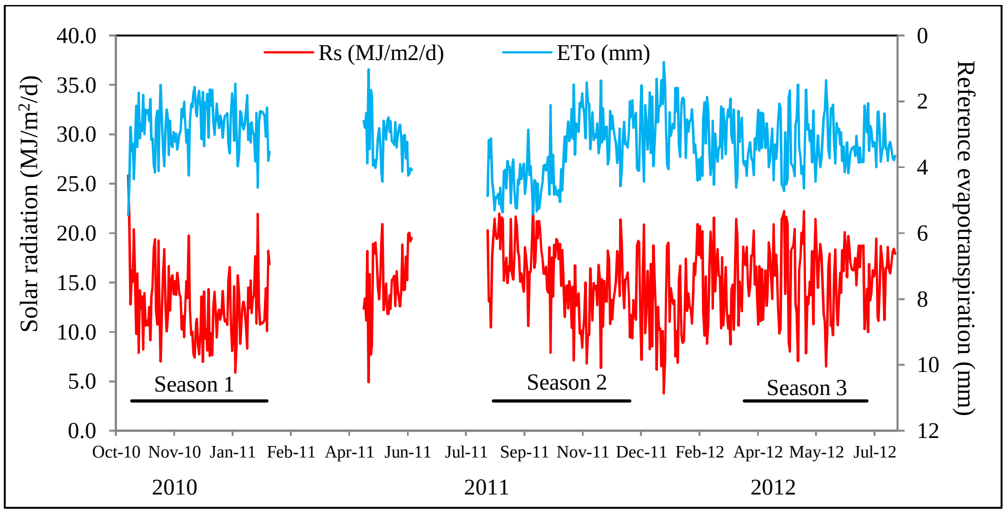


Figure 15. Daily solar radiation and reference evapotranspiration (ETo)

Figure 14 shows changes in daily average air temperature and relative humidity during the three cropping seasons. Both air temperature and relative humidity fluctuated and they had a negative correlation. Meanwhile, solar radiation and ETo also fluctuated during the three cropping seasons with a positive correlation between them as shown in Figure 15.

Monthly monitoring data

Trends of monthly average air temperature among the cropping seasons were different (Figure 16). Trends of average air temperature differed among cultivation periods. In the first and third seasons, temperature increased from the initial to the middle of period, and then decreased until the end of the period. Meanwhile, in the second cropping season, temperature increased from the early to the end of cultivation period. In addition, the average air temperature for the first cropping season was the lowest among the seasons.

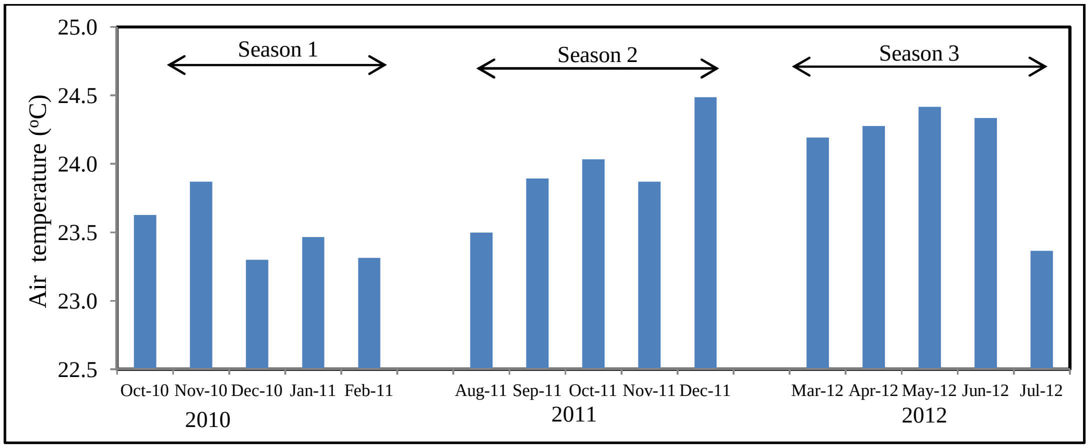


Figure 16. Monthly average of air temperature during three cropping seasons

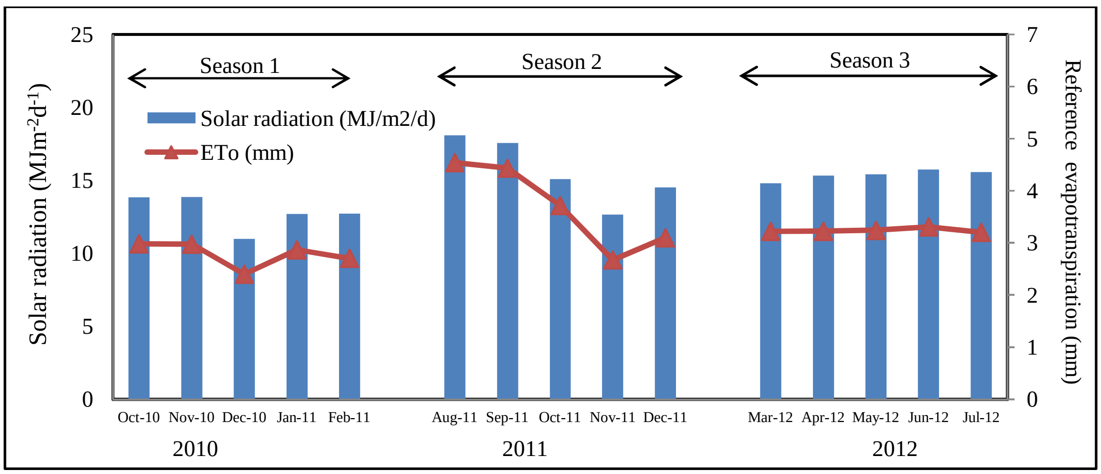


Figure 17. Monthly average of solar radiation and reference evapotranspiration (ETo)

In the first cropping season, the average solar radiation and ETo were also the lowest among the seasons (Figure 17). Both the solar radiation and ETo decreased during cultivation period particularly in the first and second cropping seasons. On the other hand, the solar radiation and ETo increased in the third cropping season. The highest solar radiation and ETo occurred on August 2011, while the lowest occurred on December 2010.

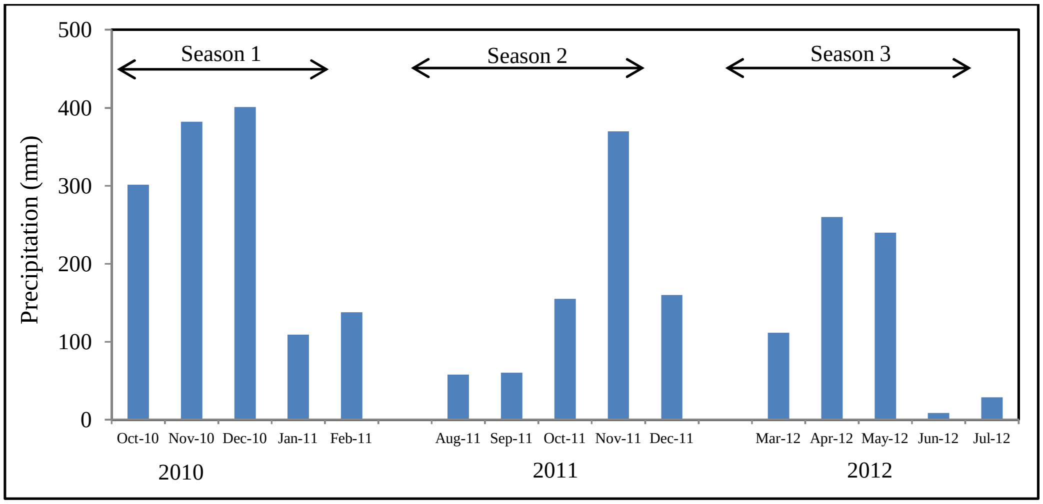


Figure 18. Monthly precipitation during three cropping seasons

Total precipitation in season 1 was the highest, while that for the third season was the lowest among the seasons (Figure 18). The highest value occurred on December 2010 with a total precipitation of 400.8 mm in the rainy season, while the lowest value occurred on June 2012 with a total precipitation of 8.8 mm in the dry season. Cumulative precipitation was 1332 mm, 626 mm, and 551 mm for the first, second and third cropping seasons, respectively. The precipitation data showed the starting time of the rainy and dry seasons as reported in the previous study (Irsyad 2011).

2.3.4 Dynamic changes in soil parameters

SRI water management in which non-flooding water is applied in the field was different from the conventional paddy cultivation. Commonly, soil moisture was kept in between saturated and field capacity conditions, thus an aerobic condition was created in which the plant can optimally absorb oxygen. However, in fact, the soil moisture fluctuated in each plot (Figure 19 and Figure 20). Sometime the soil moisture was higher than the saturated condition and sometimes it was lower than the field capacity condition.

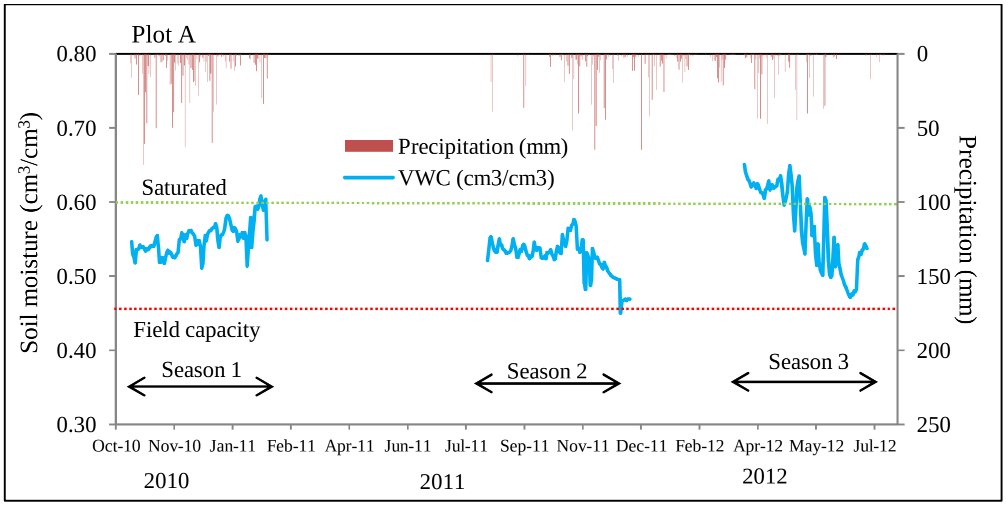


Figure 19. Daily changes of soil moisture and precipitation during three cropping season in plot A

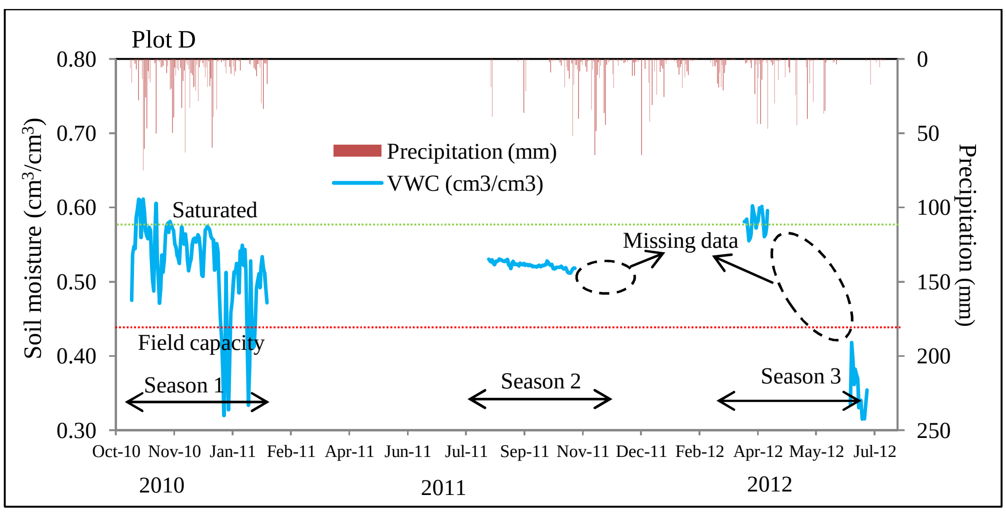


Figure 20. Daily changes of soil moisture and precipitation during three cropping season in plot D

In plot A, the soil moisture increased from the initial to the late period in the first cropping season. On the other hand, the soil moisture decreased from the initial to the late period in the second and third cropping seasons. In addition, in the third cropping period, the soil moisture was higher than the saturated border in the initial period that indicating shallow standing water occurred in the field.

In plot D, the soil moisture decreased from the initial to the end of period particularly in the first and third cropping seasons. The soil moisture was lower than the field capacity border particularly in the last period. Unfortunately, the soil moisture data were lost in the middle of period in the third cropping season as well as the last period of the second season. This was due to unexpected problems, i.e., the soil sensor was broken or the cable of sensor was unplugged from the logger.

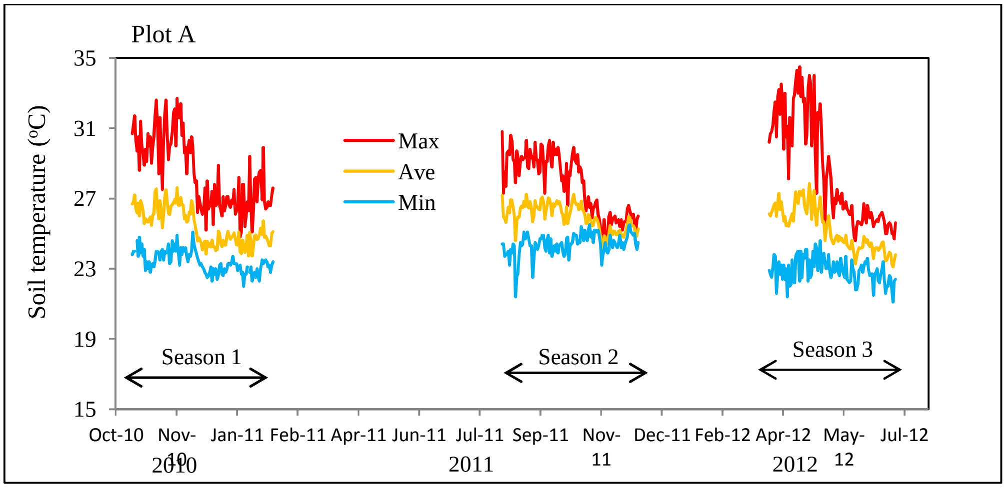


Figure 21. Daily changes of soil temperature during three cropping season

Soil temperature changes had similar trends among the cropping seasons. In the initial to middle period, soil temperature was higher than in the last period as well as its gap between maximum and minimum values (Figure 21). This result indicated that soil temperature was affected by the plant cover. In the initial to the middle period, soil temperature was higher than that in the last period because plant did not yet covered the entire field. Meanwhile, when the entire field was covered by the plant in the last period, the soil temperature fluctuation gradually weakened.

2.4. Discussion

In fact, there are two methods of field monitoring that can be applied, i.e., real-time and quasi real-time monitoring. For the application in the real field, each method has advantages and disadvantages as well.

By real-time monitoring, field condition could be monitored directly and continuously real-time in terms of field image and numerical data. Therefore, the users could identify the real situation in the field real-time without time delay. In agricultural field, real-time monitoring is required in particular for the food safety of imported food such as spinach imported from Thailand to Japan (Honda et al 2008). By real-time monitoring, customers could monitor the practices of producers in the field by real time images. However, this method is only appropriate in the area with good infrastructure especially for power source and Internet connection. In addition, this system is more expensive for the cost of electrical power and Internet connection.

In Indonesia, paddy fields are commonly in the open area and far from the farmer's house. Thus, it is difficult to find electrical source for field monitoring. Real-time monitoring using FS has been installed in SRI paddy field in Indonesia as reported in the previous studies (Setiawan et al. 2010; Gardjito et al. 2008). The system was installed in the field close to the farmer's house to get electrical power and Internet connection through phone line. By this system, the users could monitor SRI practices in the field by the farmer real time. However, the system worked well only few months and faced to some problems related to the stability. Some images data were lost when the electricity in the farmer's house was down and Internet connection was interrupted. This situation was occurred several times particularly when heavy rain and lightning occurred. Therefore, real-time monitoring is less appropriate installed for monitoring paddy fields particularly in Indonesia.

By this study, we initiated to apply new technology of field monitoring for SRI paddy field in Indonesia by adopting quasi real-time monitoring using FieldRouter. During the three cropping seasons, hourly, daily, and monthly of field conditions were monitored properly by the developed FMS connected to the meteorological and soil data loggers. Although this monitoring did not send real-time data, the data were stored in the field data loggers and sent daily to the server. Daily field image was useful to observe plant growth, while the daily field numeric data, i.e., meteorological and soil moisture data, were required as basic information to optimize SRI water management. From this experiment revealed that quasi real-time monitoring was more power saving and Internet cost effective than the real time monitoring by using the FS developed in the previous study (Manzano et al. 2011; Mizoguchi et al. 2008).

However, the stability of FieldRouter depends on the field solar power supply and the Internet connection. In case there are any problems in the coverage of the Internet connection within the data transmitting time, the plant images data are lost as shown in Figure 10. Moreover, data were also lost when the data logger battery was depleted or the sensor cable was unplugged from the logger or the sensor was broken.

In this monitoring, it was relatively easy to determine each plant growth stage (Figure 11). In addition, the numeric data showed the reasonable values for both the meteorological and the soil parameters. The data are important for further analyses particularly to evaluate effects of irrigation regime on yield and water productivity, and then to determine the optimal regime to maximize yield and water productivity.

2.4 Conclusions

The developed FMS was effective, efficient and reliable in monitoring SRI paddy field in Indonesia. The actual field conditions were monitored well in term of image, numeric and graphic data acquisition. Although this monitoring did not send real-time data, the data were stored in the field data loggers. By adopting quasi-real time monitoring, it was more power saving and Internet cost effective than the real time monitoring. The FMS has collected the important data during the three cropping seasons with different weather conditions and irrigation regimes. The data were then used for further analyses to optimize SRI water management in Indonesia.

Chapter 3: Soil Moisture Estimation in SRI Paddy Field using Neural Network

3.1 Background

In paddy field, soil moisture represents water availability for the plants and it is required for irrigation scheduling and water resource allocation, management, and planning. Soil moisture variation affects the patterns of evapotranspiration, runoff and deep percolation in paddy field (Kim et al. 2009; Reshmidevi et al. 2008; Li and Cui 1996). At the same time, soil moisture level is predominately influenced by water input through precipitation and irrigation.

From the evaluation of feasibility of FMS for SRI paddy field in Indonesia, the system faced to the constraints such as the lost data of soil moisture due to unexpected problems (Figure 20, chapter 2). In fact, the lost soil moisture data can be estimated by performing water balance analysis using hydrological data such as crop evapotranspiration, deep percolation, runoff and irrigation water (Kim et al. 2009; Reshmidevi et al. 2008). However, available water balance data are often limited because the measurements in the field are costly, complicated, and time consuming. Therefore, estimation of soil moisture is needed using another method.

Here, we propose neural network (NN) model to estimate soil moisture by considering meteorological data. NN model is more suitable for dealing with complex systems, such as agricultural systems, than mathematical methods (Hashimoto 1997). The NN has the capability to recognize and learn the underlying relations between input and output without explicit physical consideration (Basheer and Harmeer 2000). The main benefits of using the NN model are the ability to learn and then generalize the problem (Nugroho 2003). In agricultural fields, the NN has been applied to classify irrigation planning strategies (Raju et al. 2006) and to estimate subsurface wetting for drip irrigation (Hinnell et al. 2009) .

The main objectives of this chapter were to estimate soil moisture by using meteorological data in SRI paddy field on daily basis using NN model, and then to validate the proposed model by comparing observed and estimated values of soil moisture.

3.2 Methodology

3.2.1 Training and Validation data

The data set for training and validation processes for development of NN models came from the field experiment in the SRI paddy field particularly in the first and second cropping seasons of plot A (Table 2, chapter 2). The first season data were used for the training process, while those in the second season were used for the validation process. These processes as a whole are called the cross validation (Suhardiyanto et al. 2009; Morimoto and Hashimoto 2000). Then, the NN model was used to estimate the missing soil moisture data for plot D in the third cropping season (Figure 20, chapter 2).

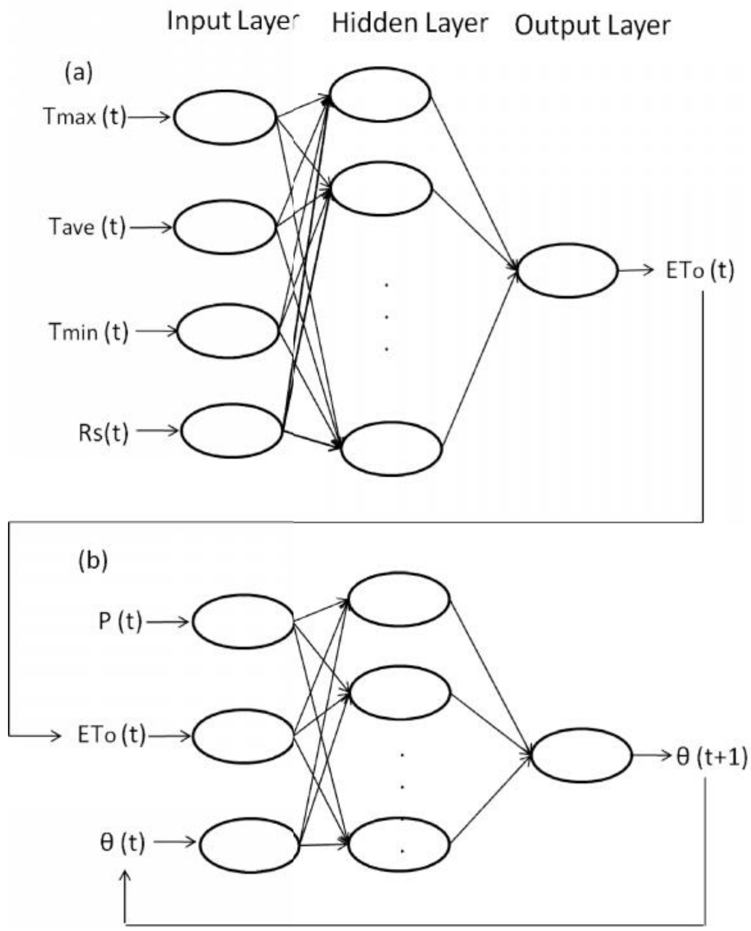
3.2.2 Development of Neural Network Model

Two NN models were developed by integrating three layers, i.e., input, hidden and output layers (Figure 22). The first model was developed to estimate ETo according to maximum, average, and minimum values of air temperature and solar radiation.

For validation of the first model, the output of NN model was compared to ETo calculated by the FAO Penman-Monteith model (Allen et al. 1998) as a model for the evapotranspiration validated by lysimeter observations (Persaud et al. 2007). Here, we used daily average values of air temperature, wind speed, relative humidity, and total solar radiation to calculate ETo expressed by the following equation:

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad (2)$$

where, ETo is reference evapotranspiration (mm), R_n is net radiation at the crop surface ($MJm^{-2}d^{-1}$), G is soil heat flux density ($MJm^{-2}d^{-1}$), T is mean daily air temperature (°C), u_2 is wind speed at 2 m height (m/s), e_s is saturation vapour pressure (kPa), e_a is actual vapour pressure (kPa), Δ is slope vapour pressure curve (kPa°C^{-1}), and γ is psychrometric constant (kPa°C^{-1}).



Note:

Tmax : Maximum air temperature (°C)

Tave: Average air temperature (°C)

Tmin: Minimum air temperature (°C)

P: precipitation (mm)

ETo: reference evapotranspiration (mm)

Ɵ: soil moisture (cm^3/cm^3)

Figure 22. NN model of the current study: a) ETo estimation, b) soil moisture estimation in SRI paddy field

The second NN model was developed to estimate soil moisture according to the estimated ETo and precipitation. For this estimation, dynamics of NN model, similar to an auto-regressive moving average model procedure, was adopted by considering historical output data (Morimoto et al. 2007; Chen et al. 1990).

In both NN models, all input parameters data were normalized between 0 and 1 by using fixed minimum and maximum values. Normalization of data is important to avoid larger numbers from overriding smaller ones and to prevent premature saturation of hidden nodes, which impedes the learning process (Basheer and Harmeer 2000). For the hidden layer, total nodes of 3 and 6 were selected as moderate number for the first and second models to prevent excessive time-consumption in the training process and to avoid incapability in differentiation between complex patterns due to few numbers of node in the hidden layer.

Back propagation was selected as the learning method, which is composed of two phases; first, propagation (forward and backward propagation), and second, weight update. A sigmoid function was selected as the activation by the following equations:

$$f(y) = \frac{1}{1 + e^{-gy}} \tag{3}$$

$$y = \sum_{i=0}^{n} x_i w_i \tag{4}$$

where x_i, w_i, n, g are the inputs, weights, number of inputs and gain parameter, respectively.

The gain parameters are usually set to 1.0 and not changed by the learning rule. However, this fixed value probably caused a local minima problem. Therefore, the gain parameter should be adjusted according to the degree of approximation to the desired output of the output layer (Wang et al. 2004). Here, the gain parameter is adjusted based on the following condition:

$$g = \frac{1}{AP} \text{ if } AP > 1.0 \tag{5}$$

$$g = 1.0 \quad \text{if } AP \leq 1.0 \tag{6}$$

$$Ap = 2e_p \tag{7}$$

$$e_p = \max\left|t_p - o_p\right| \tag{8}$$

where Ap is degree of the output layer, e_p is error for pattern *p*, t_p and o_p are observed and estimated output for pattern *p*, respectively.

Both NN models were developed in Microsoft Excel 2007 with Visual Basic using our own codes. The details of the codes can be referred in Appendix 4. Here, we used the indicator of coefficient of determination (R^2) to evaluate the models by comparing observed and estimated values and its significance (p value). The value of R^2 ranged from 0.0 to 1.0 with higher values indicating better agreement. However, sometimes R^2 is not ideal for this comparison where it containing bias. Thus, we also used mean squared deviation (MSD) that consisting squared bias, squared difference between standard deviations, and lack of correlation weighted by the standard deviations (Kobayashi and Salam 2000).

3.3 Results and Discussion

3.3.1 Interface of the NN model

The interface of the NN model was developed in Microsoft Excel 2007 as shown in Figure 23. There are five parts, i.e., NN parameters, button, data, graphics, and accuracy of model. The NN parameters contained the constant of learning parameters, number of iterations, number of layers, numbers of node inputs, hidden and outputs layers. All these parameters should be determined before running the model. The button part contains the buttons to run the model, i.e., the button of initialization to generate the weights, the button of training to run training process and the button of validation to start validation process. The data part presents the initial and the end result of the weight, the output data between estimated and observed data both for training and validation processes. The graphics part presents three graphics, i.e., the error during iteration, results of training process and validation process. Accuracy of model is shown as R^2 values for both training and validation processes.

Before running NN model, the data for training and validation processes should be inputted into the sheets of “Data Training” and “Data Validation”. Then, the initial values of weight are determined by clicking the button of initialization. Initial values of weights will be presented in the data part. After that, the training process is performed by clicking the button of training. The program automatically runs and stops after repeating a number of iterations. Results of training process are automatically presented in the interface in term of the graphic error, graphic of training process, the estimated data, the weights, and R^2 of training process. The last process is validation process by clicking the button of validation. Results of validation are presented in the estimated data, graphics of validation process, and R^2 of validation process.

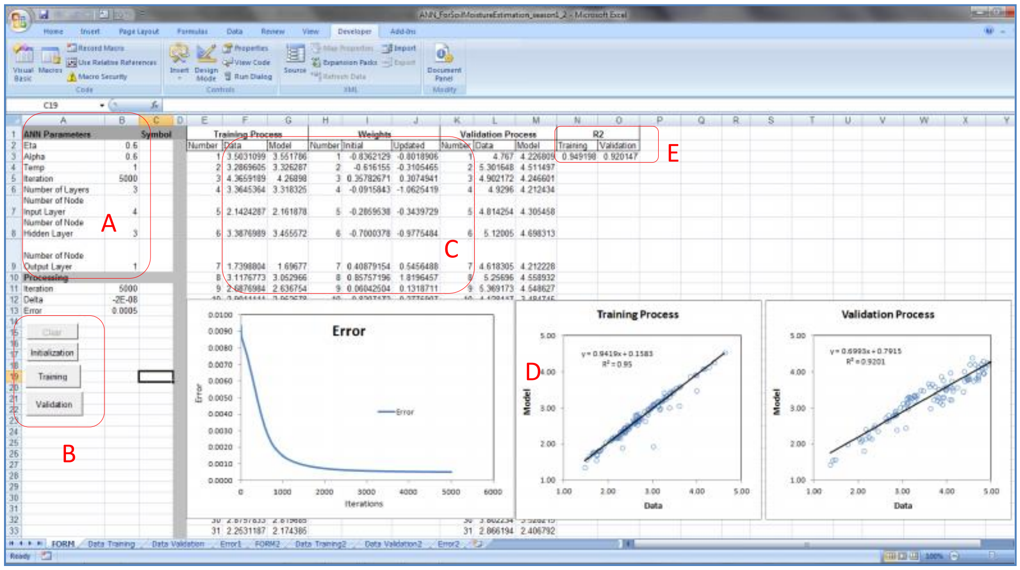


Figure 23. The interface of NN model: A. NN parameters, B. Button, C. Data, D. Graphics, E. Accuracy of model

3.3.2 Estimation of reference evapotranspiration

The training process of the NN model was performed with 5000 iterations. The training process should be carried out firstly by the NN model to learn the pattern between input and output. After 5000 iterations, the NN model estimated ETo with the R^2 of 0.95 ($p<0.01$) (Figure 24). This means that more than 90% of the changes in observed ETo could be described by the model. Also, MSD between estimated ETo by the NN model and Penman-Monteith was low (0.02) with squared bias<0.001 mm. Therefore, the weights, the representation of relationship between the input and the output, can be used to estimate ETo in paddy field with maximum, average and minimum values of air temperature and solar radiation.

After performing the training, the validation can be further performed using the weights from the training. Estimated ETo was directly calculated using the NN model and the result is shown in Figure 25. The correlation between estimated ETo by the NN model and Penman-Monteith was shown as R^2 of 0.92 ($p<0.01$), lower than that for the training process. In addition, MSD was higher than that training process with squared bias of 0.11 mm.

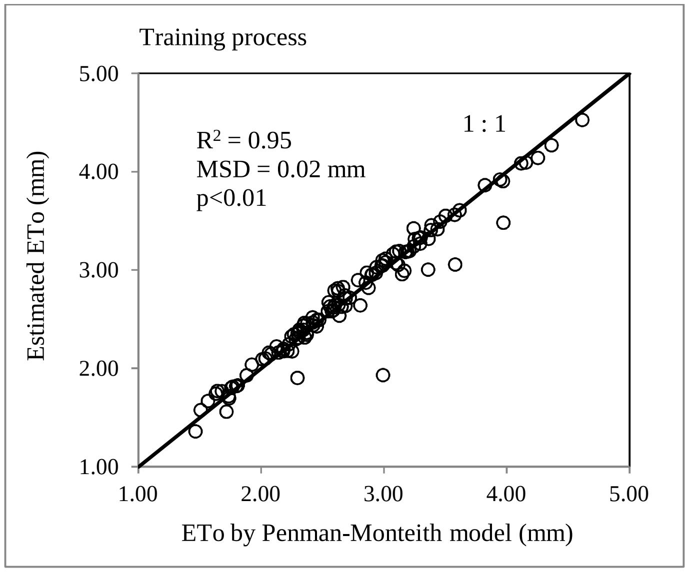


Figure 24. The result of training NN model to estimate reference evapotranspiration

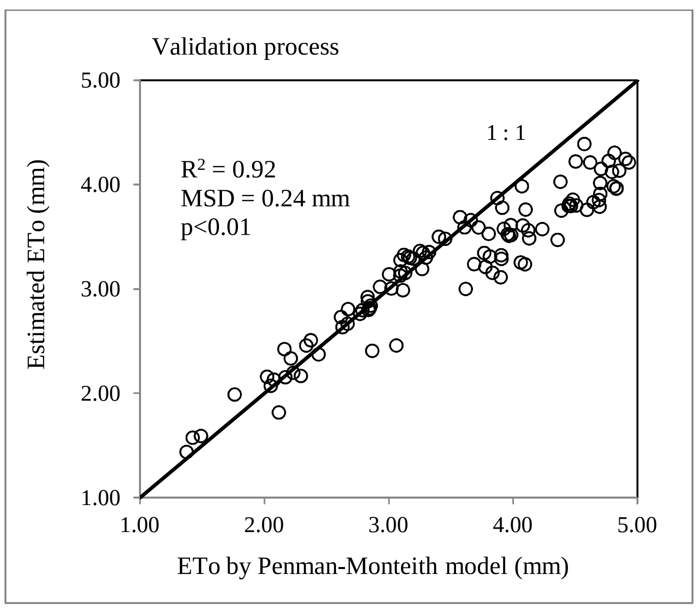


Figure 25. The result of validation of NN model to estimate reference evapotranspiration

The accuracy of a validation process is commonly lower than that for the training process when cross validation is adopted. Although it was lower than that for the training process, resulting in R^2 of 0.92 ($p<0.01$), the accuracy of the model was thought to be acceptable since more than 90% of the variability of observed data could be well predicted by the model.

The high accuracy of the model both for training and validation processes indicated that ETo is mainly affected by both solar radiation and air temperature. This was supported by the monitoring data as presented in the previous chapter that ETo has a positive correlation to solar radiation and air temperature was affected by solar radiation.

Air temperature is the basic variable that required for ETo estimation (Hargreaves and Allen 2003). Meanwhile, solar radiation is the most sensitive variable for ETo estimation (Hupet and Vanclooster 2001). By observing the study sites, NN model was widely used to estimate ETo with some combinations of meteorological variables as the input. For example, NN model was developed to estimate ETo with some scenarios of variables input under Burkina Faso climatic conditions (Traore et al. 2010). They found that NN model with multilayer feedforward neural network trained by back propagation learning method as selected in this study was more accurate than analytical method by Hargreaves model.

3.3.2 Estimation of soil moisture

The NN model estimated soil moisture with MSD of 0.0001 and 0.0002 cm^3/cm^3 for the training and validation processes, respectively (Figure 26 and Figure 27). The values of MSD were low indicated that between observed and estimated of soil moisture were very close, thus the trends of observed and estimated soil moisture were similar and a tight linear correlation between them were observed. In the training process, however, over estimation was occurred particularly in the last cultivation period (Figure 26), thus R^2 the model was lower than the first model.

The model accuracy of the validation process was also lower than that of the training process. Figure 27 shows the correlation between observed and estimated values of soil moisture in the second cultivation period as the result of validation process. In the validation process, estimated soil moisture was calculated according to the weights values from training process with the total numbers of 24. Although over and under estimation were also occurred when estimating soil moisture, a tight correlation was shown in the figure with R^2 values of greater than 0.70 and MSD of lower than 3×10^{-4} cm^3/cm^3. Accordingly, the estimation results in this study showed good agreement to the observed data, thus the proposed method was reliable as suggested by the previous study (Kim et al. 2009). NN model represents "black-box" model and proneness to over fitting (Tu 1996), thus it is difficult to find the reason of over and under estimation during training and validation processes. We supposed that situation was occurred because soil moisture fluctuation was not only affected by meteorological variables, but also other hydrology variables such as irrigation water, percolation and runoff. In irrigated paddy field, the NN model accuracy might be improved by considering water balance variables such as irrigation water, percolation, and runoff, therefore the generalization ability of NN model could be improved in extracting the significant variables to estimate soil moisture.

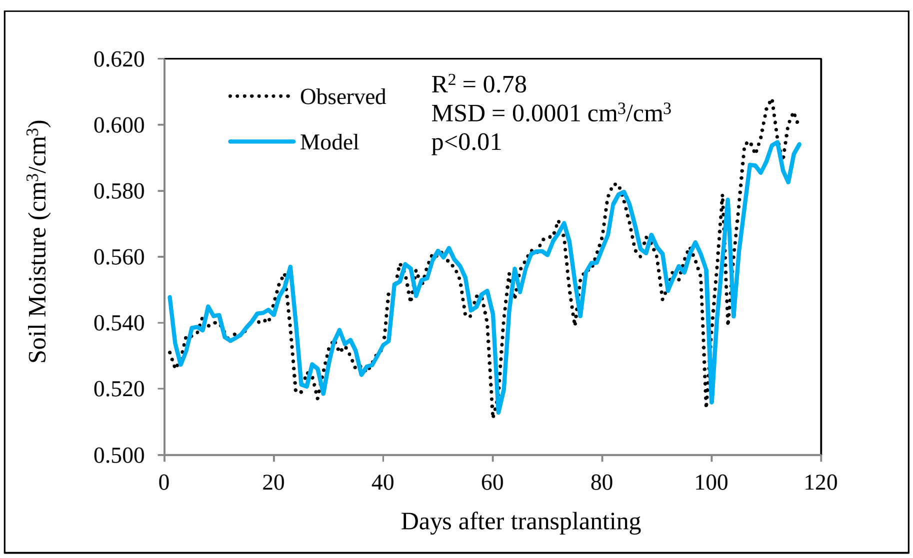


Figure 26. Observed and estimated values of soil moisture by the NN model established in the training process

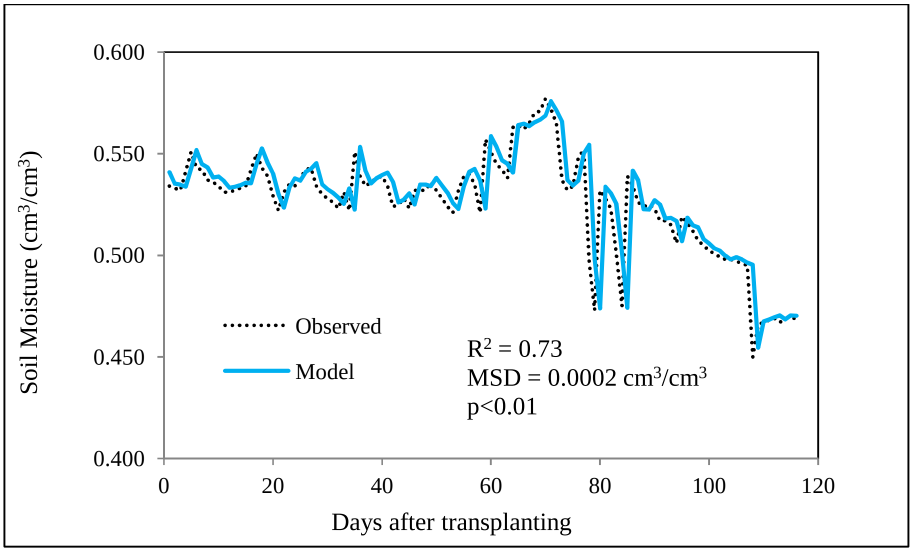


Figure 27. Observed and estimated values of soil moisture by the NN model established in the validation process

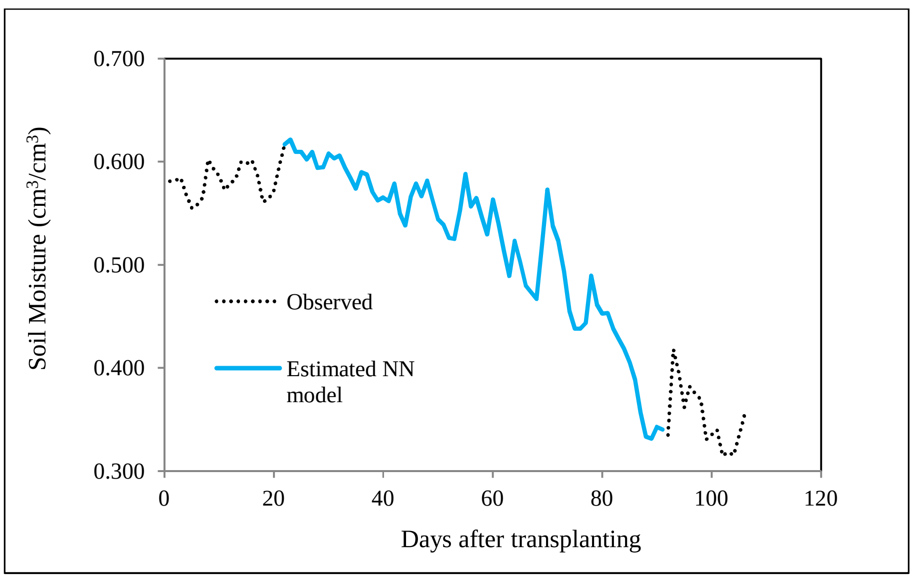


Figure 28. Estimated soil moisture in plot D in third cropping season by the NN model

After conducted the training and validation processes according to the data from plot A, we performed the estimation process to estimate missing soil moisture data in plot D in the third cropping season with the results presented in Figure 28.

The estimated soil moisture fluctuated and its value decreased until the end of the cultivation period. However, during a particular time, soil moisture increased as observed on the 55 and 70 DAT. The increase in soil moisture was thought to be caused by large amounts of precipitation of 40.4 mm and 35.0 mm, respectively.

3.4 Conclusions

This chapter proposed neural network (NN) model to estimate reference evapotranspiration and soil moisture in SRI paddy field using meteorological data. In the first model, ETo was estimated accurately by the NN model with R^2 of 0.95 and 0.92 and MSD of 0.02 mm and 0.24 mm for training and validation processes, respectively. Then, the second model estimated soil moisture with MSD values were very low both for training and validation processes ($< 3\text{x}10^{-4}$ cm^3/cm^3). The results suggested that the NN model was reliable to estimate soil moisture in SRI paddy field with meteorological data and without complicated and expensive tools, heavy labor and time consumption. The model can also be used to estimate the missing soil moisture data from field monitoring as was seen in plot D in the third cropping season.

Chapter 4: Field Monitoring Data for Estimating Non-Measurable Water Balance Variables

4.1 Background

Under alternate wetting and drying irrigation (AWDI), SRI paddy field is not kept saturated continuously but is allowed to be dry intermittently during certain growing stages. However, when alternate wet and dry irrigation is adopted for rice production, the optimal timing and duration of wet and dry conditions are unclear during actual cultivation. Therefore, optimization of water management is the main challenge in maintaining the sustainability of rice farming with less water input. Empirical optimization processes can be attempted by comparing different irrigation regimes in different paddies and evaluating these regimes by determining water balance variables, to clarify relationships among the water productivity and water use efficiency.

Evaluation of irrigation regimes is important as the first step to identify the effect of the regimes on yield and water productivity. For this purpose, the information of water balance variables, such as irrigation water and crop evapotranspiration, are needed. However, during monitoring time, those data were not available in the field. When measurement data are limited, estimation of non-measurable water balance variables is an important alternative if the available measured data and an appropriate water balance model can be combined.

When performing such estimation, variables that have cause-and-effect relationships among the estimated and measurable variables must be considered. Soil moisture, the main determinant of water availability to the plants, affects the pattern of water balance variables such as crop evapotranspiration, percolation, and runoff in paddy field (Kim et al. 2009; Reshmidevi et al. 2008; Li and Cui 1996). At the same time, soil moisture is predominately influenced by precipitation and irrigation water. Therefore, soil moisture should be the most useful component when estimating non-measurable water balance variables, because soil moisture reflects causes as well as effects, and thus has close relationships with water balance variables. In addition, soil moisture can be easily measured in paddy field under AWDI using readily available soil moisture sensors (Manzano et al. 2011).

Here, we propose a linear program method using Excel Solver, which is incorporated into Microsoft Excel, to estimate non-measurable data. Excel Solver is a software tool that helps users find the best way to allocate scarce resources by searching algorithms. It has sufficient power to find the coefficients to fit the data in non-linear equations (Walsh and Diamond 1995) such as chromatographic peak resolution (Dasgupta 2008), enzyme activity values (Abdel-Fattah et al. 2009) and molar absorptivities of metal complexes and protonation constants of acids (Maleki et al. 1999). Moreover, it has ability to estimate up to 200 data within one process. Accordingly, it can be used to estimate non-measurable water balance variables by combining measurement data and model.

The objective of this chapter was to examine the linear program with Excel Solver method for estimating non-measurable water balance variables, such as irrigation water, crop evapotranspiration, percolation, and runoff, under different irrigation regimes, by considering observed soil moisture.

4.2 Methodology

4.2.1 Data collection by the FMS

The data to estimate water balance variables were collected through the FMS as explained in chapter 2. To confirm the accuracy of the proposed method, we used the data in the third cropping season. Here, during cultivation period, growth stage was divided into four stages, i.e., initial, crop development, mid-season, and late season stages (Vu et al. 2005; Tyagi et al. 2000; Allen et al. 1998; Mohan and Arumugam 1994).

As explained previously, we classified the field conditions into three levels, i.e., wet (W), medium (M) or dry (D). According to the field experimental data in the third cropping season, the average soil moisture and its level in each plot is presented in Table 5.

As shown in Table 5, even if plot A and plot C were classified to be the same in each growth stage, as in the case of plot B and plot D, however, the average soil moisture levels among the plots were different. Thus, the water balance variables were also different among them.

Table 5. The average of soil moisture in each growth stage in the third cropping season

Growth stage	Average soil moisture (cm^3/cm^3)			
	Plot A	Plot B	Plot C	Plot D
Initial	0.622 (W)	0.602 (W)	0.611 (W)	0.586 (W)
Crop development	0.592 (W)	0.585 (W)	0.593 (W)	0.563 (W)
Mid-season	0.522 (M)	0.488 (M)	0.472 (M)	0.455 (M)
Late season	0.505 (M)	0.401 (D)	0.456 (M)	0.350 (D)

4.2.2 Estimation procedures

Water balance was analyzed according to the scheme in Figure 29. Here, observed soil moisture (θ_o) and meteorological data were used to estimate the variables consisting of irrigation water (I), crop evapotranspiration (ETc), percolation (DP), and runoff (Qr) according to the schematic diagram for estimation processes in Figure 30. Table 6 summarizes of measured, calculated, and estimated variables in this chapter. We assumed the soil was homogenous, thus observation-based soil water storage (S_o) was determined by multiplying observed soil moisture by the effective soil depth (Zr). Before performing the estimation, initial values of estimated variables for each day were determined as described later. Then, model-based soil water storage (S_m) was determined by performing water balance analysis. The inflow to the field consisted of precipitation and irrigation water, while outflow crop evapotranspiration, runoff and percolation. We defined runoff as the lateral water movement from the inside to the outside of the experimental plot. Accordingly, water balance equation at time can be expressed as:

$$S_m(t) = S_m(t-1) + \Delta S(t) \quad (9)$$

$$\Delta S(t) = P(t) + I(t) - Qr(t) - DP(t) - ETc(t) \quad (10)$$

where S_m is model-based soil water storage (mm), ΔS is the change of soil water storage (mm), P is precipitation (mm), I is estimated irrigation water (mm), Qr is estimated runoff (mm), DP is estimated percolation (mm) and ETc is estimated crop evapotranspiration (mm).

Table 6. Measured, calculated and estimated variables

No	Variables	Measured	Calculated	Estimated	Method
1	Observed soil moisture (θo)	√			5TE soil sensor
2	Precipitation (P)	√			Rain gauge
3	Referece evapotranspiration (ETo)		√		Penman-Monteith model
4	Crop evapotranspiration (ETc)			√	Excel Solver
5	Irrigation water (I)			√	Excel Solver
6	Runoff (Qr)			√	Excel Solver
7	Percolation (DP)			√	Excel Solver
8	Observation-based soil water storage (So)		√		Model (So = θo x Zr)
9	Effetive soil depth (Zr)	√			Field observation
10	Model-based soil water storage (Sm)		√		Equations 9-10
11	Initial value of ETc (ETc_{ini})		√		Equation 14
12	Initial value of I (I_{ini})		√		Equations 17-18
13	Initial value of Qr (Qr_{ini})		√		Equations 15-16
14	Initial value of DP (DP_{ini})		√		DP_{ini} = 1.5, if Soil moisture level is wet DP_{ini} = 1 , if soil moisture level is medium DP_{ini} = 0.5, if soil moisture level is dry

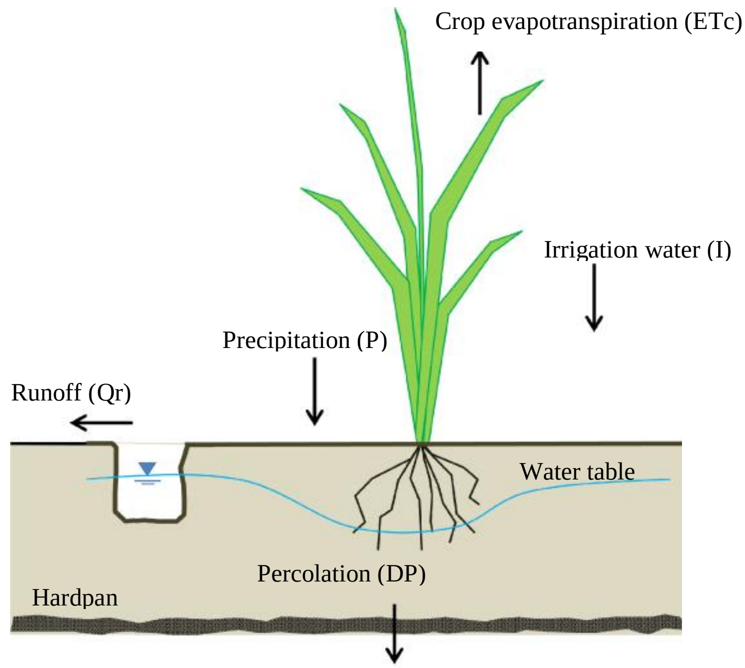


Figure 29. Water balance scheme in paddy field

Linear program with Excel Solver was used to estimate those variables because it had the ability to estimate non-measurable variables by minimizing the *Error* as the difference between the observation-based soil water storage and the model-based soil water storage. However, within one process, it can involve up to 200 of estimated data only. Hence, the data set through the entire cultivation period was divided into four data sets based on the growth stages. Total days for the initial, crop development, mid-season and late season stages were 24, 40, 23, and 18, respectively. The total numbers of estimated data for the growth stages were, therefore, 96, 160, 92 and 72 data, respectively.

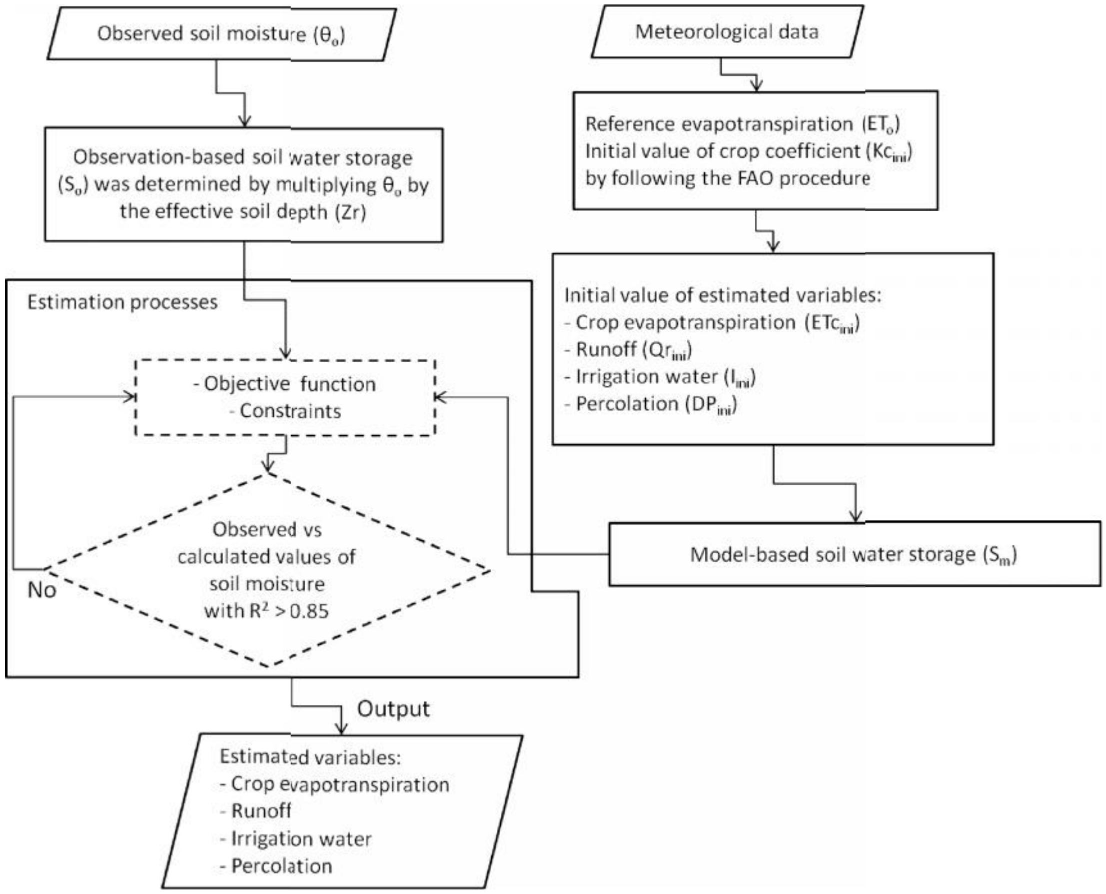


Figure 30. Schematic diagram for the estimation of non-measurable water balance variables

4.2.3 Linear program estimation with Excel Solver

Excel Solver, an analysis tool incorporated into Microsoft Excel 2007 for Windows, is a software tool that helps users find the best way to allocate scarce resources. It works by searching algorithms in a spreadsheet environment, in which the users can follow the procedures based on its guidelines (Morrison 2005; Walsh and Diamond 1995). Excel Solver is a kind of linear program method, thus in this study, estimation process was formulated by the following linear program:

Objective function:

Minimize the following equation:

$$Error = \sum_{t=1}^{n} \left| S_o(t) - S_m(t) \right| \tag{11}$$

Constraint to:

$$ETc_{min} \leq ETc(t) \leq ETc_{max} \quad (12)$$

$$Qr(t) \geq 0; I(t) \geq 0 \quad (13)$$

where, S_o is observation-based soil water storage (mm), t is time and n is the total number of days in the growth stage (d), ETc_{min} is minimum crop evapotranspiration, ETc_{max} is maximum crop evapotranspiration. ETc_{min} and ETc_{max} were given by multiplying ET_o by the minimum (0.2) and maximum (1.6) values of crop coefficient, respectively. The minimum crop coefficient of 0.2 was the crop coefficient for bare soil (Allen et al. 1998) and the maximum value of 1.6 was used since this value was greater than ever observed maximum value (<1.5) of crop coefficient for rice paddy under continuous submergence in which the values of crop coefficient are known to be greater than those under non-flooding condition (Tyagi et al. 2000).

4.2.4 Initial values of non-measurable variables

In the cultivation period of 105 days, four initial values for each day were inputted as first values for the estimated variables. Accordingly, the total number of the initial values for each variable was 105 as explained below.

1. Crop evapotranspiration

The initial value of crop evapotranspiration for each day was determined according to the following equation (Allen et al. 1998) which takes changes in evapotranspiration associated with the plant growth into account:

$$ETc_{ini}(t) = Kc_{ini}(t) \times ET_o(t) \quad (14)$$

where, Kc_{ini} is the initial value of crop coefficient that varies with the crop growth stages and given based on the FAO calculation procedure.

2. Percolation

We defined percolation as a flux of vertical flow in saturated soil (Jury and Horton 2004). Percolation is primarily a function of soil texture and its rate can be reduced by reducing ponding water (Kukal and Aggarwal 2002; Tuong and Bhuiyan 1999; Kalita et al. 1992) or by application of AWDI (Van der Hoek et al.

2001). These irrigation techniques reduce percolation rate by reducing hydrostatic pressure in the field. Higher soil moisture level is correlated to the higher hydrostatic pressure and *vice versa*.

Therefore, the initial value of percolation (DP_{ini}) was given as a rate based on observed soil moisture. DP_{ini} for wet, medium and dry levels were 1.5 mm/d, 1 mm/d, and 0.5 mm/d, respectively. We gave those rates according to the similar soil conditions in which the rate was between 1 and 5 mm/d under flooding irrigation regimes (Bouman et al. 2007; Guerra et al. 1998; Sakthivadivel et al. 2001).

3. Runoff

In paddy field, runoff is a function of precipitation which has a positive correlation with runoff (Chen et al. 2003). Accordingly, we assumed that runoff occurred when precipitation was greater than the maximum reference evapotranspiration, while the initial value for each day was given as follows:

$$Qr_{ini}(t) = 0 \qquad \text{if } P(t) < ETo_{max} \qquad (15)$$

$$Qr_{ini}(t) = P(t) - ETo_{max} \qquad \text{if } P(t) \geq ETo_{max} \qquad (16)$$

ETo_{max} is the maximum reference evapotranspiration of the cultivation period.

4. Irrigation water

Irrigation water was supplied when runoff was zero on the day and the precipitation did not fill the plant water requirement mainly dominated by crop evapotranspiration because the percolation rate was thought to be low. Accordingly, for each day, the initial value was given by the following formulae:

$$I_{ini}(t) = 0 \qquad \text{if } Qr_{ini}(t) > 0 \qquad (17)$$

$$I_{ini}(t) = ETc_{ini}(t) - P(t) \qquad \text{if } Qr_{ini}(t) = 0 \qquad (18)$$

4.2.5 Model validation

R^2 value, as well as degree of significance (p value), was used as an indicator to compare between observed and calculated values of soil moisture given by the model. Here, we used the value of R^2 of 0.85 as the threshold of model acceptance (Luo et al. 2009). However, comparison between the estimated and observed variables could not be performed because we didn't measured irrigation water, crop evapotranspiration, percolation, and runoff. So, we used indirect validation to evaluate the estimation performance, i.e., linear correlation between precipitation and estimated runoff and the comparison of total inflow and outflow using percent error (% error) indicator. Also, the comparison between estimated crop evapotranspiration and crop evapotranspiration by FAO as well established method was presented in the next chapter (chapter 5) when we discussed about crop coefficient as plant response to available water in the field.

4.3 Results and Discussion

Table 7 presents model validation of the proposed method and total estimated water balance variables in each plot.

Table 7. Model validation and total water balance variables in each plot

	Irrigation regimes			
Variables	Plot A	Plot B	Plot C	Plot D
Model validation:				
R^2 value	0.95	0.97	0.94	0.97
p value	< 0.01	< 0.01	< 0.01	< 0.01
Water balance :				
Inflow:				
Precipitation (mm)*	551.0	551.0	551.0	551.0
Irrigation water (mm)**	342.6	295.1	304.9	271.9
Total inflow (mm)	893.6	846.1	855.9	822.9
Outflow				
Runoff (mm)**	413.2	427.1	417.2	422.6
Crop evapotranspiration (mm)**	366.1	356.1	355.2	355.3
Percolation (mm)**	134.3	125.7	122.7	117.0
Total outflow (mm)	913.6	908.9	895.1	894.9
% error between total inflow and outflow (%)	2.19%	6.91%	4.39%	8.05%

*observed data, **estimated data

With regard to R^2 greater than 0.85 with $p<0.01$, a significant correlation between calculated and observed values of soil moisture was observed. These degrees of significance demonstrate how well the current method functions, given the availability of a minimum set of observed variables. The reliability of the water balance model was also suggested by well-matched relationships among the inflow and outflow variables with low percent error (< 10%) for all irrigation regimes.

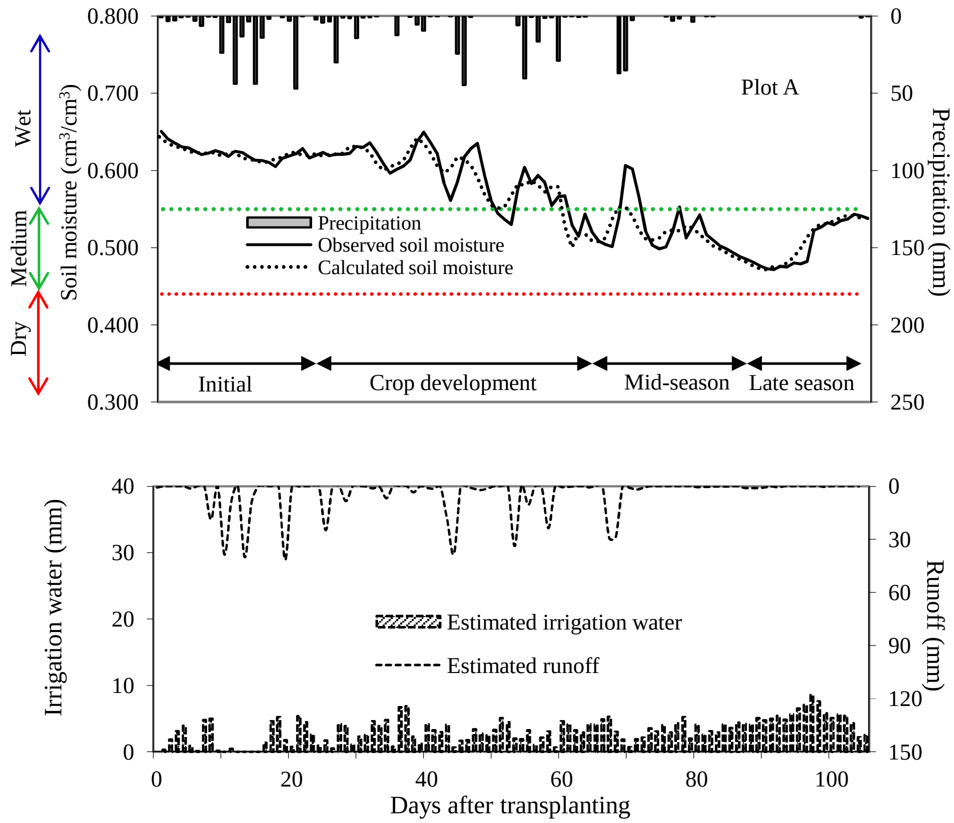


Figure 31. Observed and estimated water balance variables in plot A

The calculated and observed values of soil moisture fitted well for all regimes as presented in Figures 31-34. Over and under estimation occurred when observed soil moisture increased or decreased suddenly. This is the limitation of fitting method by linear program when it works iteratively to minimize the error. Although this situation occurred, with R^2 greater than 0.85 ($p<0.01$), the model was thought to be acceptable since more than 85% of the variability of observed soil moisture could be well estimated.

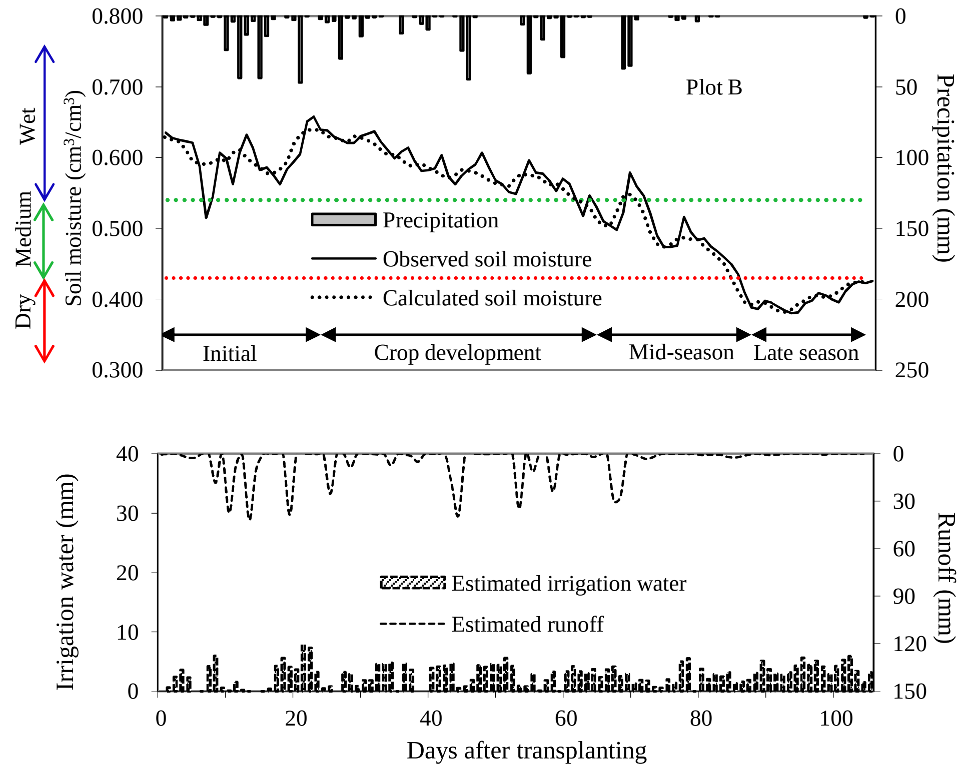


Figure 32. Observed and estimated water balance variables in plot B

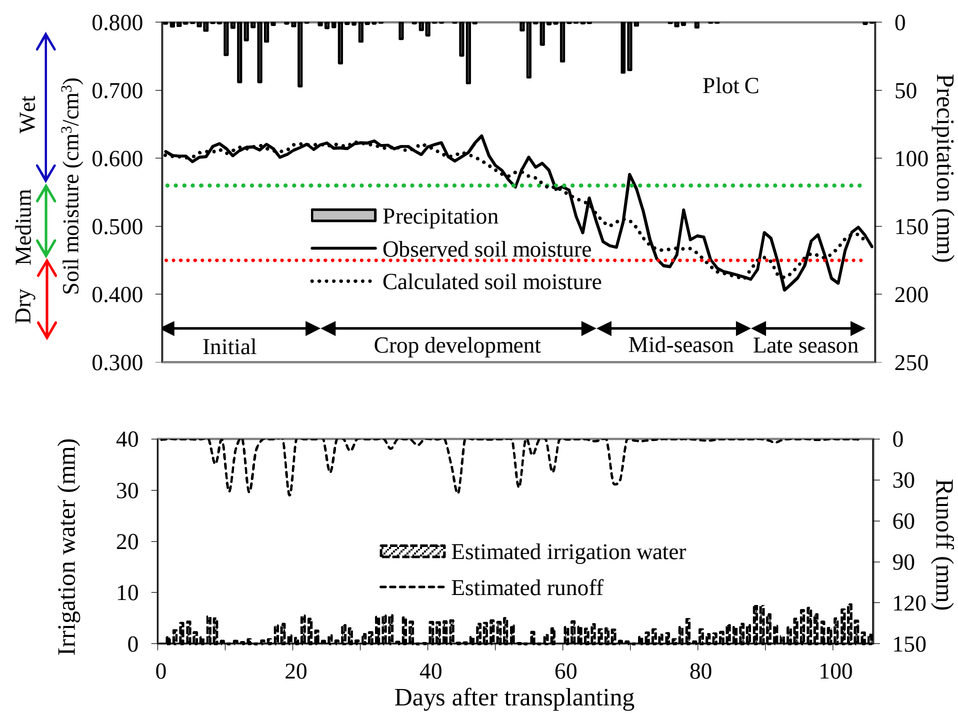


Figure 33. Observed and estimated water balance variables in plot C

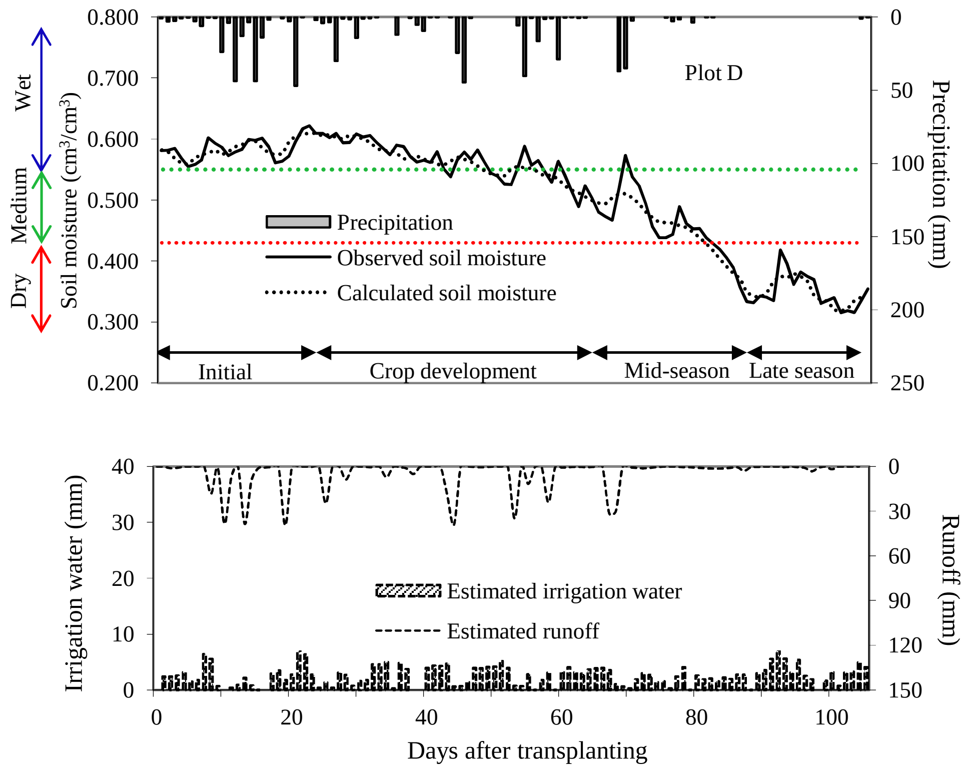


Figure 34. Observed and estimated water balance variables in plot D

As typical in humid tropical areas where precipitation amounts are large enough to saturate the paddy soil, the total estimated irrigation water was less than 38% of the total inflow, indicating the minimum irrigation required for aerobic rice cultivation in such areas (Bouman et al. 2005). The Excel Solver method estimated runoff as the dominant outflow variable, accounting for approximately 45% of the total outflow. Meanwhile, crop evapotranspiration and percolation contributed to the total outflow only approximately 40% and 15%, respectively. The low percolation was caused by lack of standing water in the field that might reduce hydrostatic pressure as reported in the previous study under AWDI (Van der Hoek et al. 2001; Bouman and Tuong 2001).

Significant correlations were also found between precipitation and estimated runoff for all regimes ($p<0.01$), indicating that the source of runoff was precipitation (Figure 35). This relationship was presented by linear equation with an R^2 value of 0.98 for all plots. This results indicated that the trends of precipitation and estimated runoff were similar for all regimes, as also reported in a previous study (Cho 2003) which showed that runoff was mainly dominated by precipitation when the percolation rate was low. The small amounts of precipitation were still remained in the field before the soil was saturated as shown by the negative intercept values in those linear equations (Figure 35).

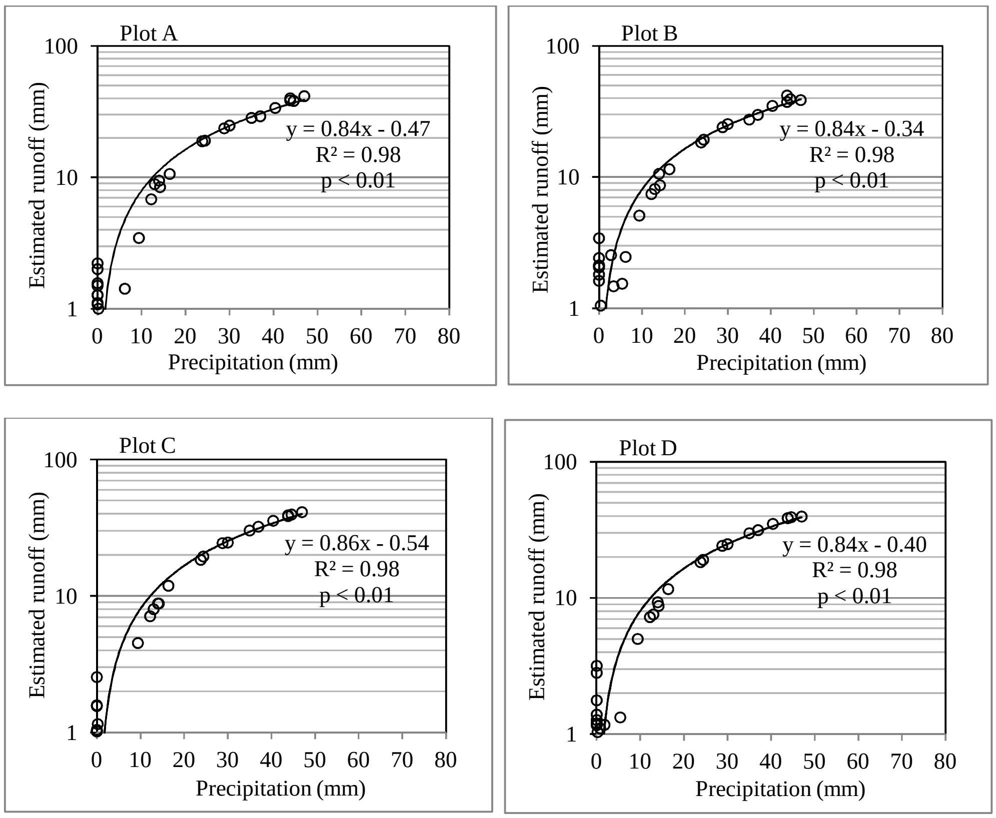


Figure 35. Correlation between precipitation and estimated runoff

Linear program by Excel Solver was well implemented for estimating non-measurable water balance components for rice cultivation in paddy field as suggested from these results. The set of estimated variables are expected to elucidate the relationships between the patterns of water balance and the physiological conditions of the crop. Consequently, optimal irrigation regimes are expected to be developed to incorporate the most suitable values for components such as crop evapotranspiration and required irrigation water, variables that crucially affect yield and water productivity under non-flooding irrigation regimes.

4.4 Conclusions

A novel method for estimating water balance variables using linear program with Excel Solver was applied to the estimation of irrigation water, crop evapotranspiration, percolation, and runoff in paddy field under different irrigation regimes particularly in the third cropping season, by considering observed soil moisture. As a result, Excel Solver estimated the variables with R^2 greater than 0.85 ($p<0.01$) between observed and calculated values of soil moisture. In addition, when indirect validation was used, the reliability of the model was shown by the significant linear correlations between precipitation and estimated runoff with R^2 of 0.98 ($p<0.01$). Also, a well-matched relationship was observed between the total inflow and outflow with low percent error (< 10%) for all irrigation regimes. Therefore, the estimated data could be used in further analyses particularly to evaluate water management in the next chapter.

Chapter 5: Crop Coefficient for SRI Paddy

5.1 Background

In Indonesia rice is commonly cultivated under continuous flooding irrigation by maintaining the depth of water between 2 and 5 cm to control weeds, to reduce the frequency of irrigation and to secure against possible future shortage of water due to the unreliable water delivery system. Therefore, the quantity of irrigation water is usually greater than the actual water requirement. This weakens water saving effects causing large amounts of surface runoff, seepage and percolation (Bouman 2001). One strategy to promote water saving without significant yield losses is to adopt AWDI (Won et al. 2005), in which the field is kept saturated or under shallow standing water and then the soil is kept dry for particular periods instead of continuously flooding.

In order to examine the adequacy of water for plant under AWDI, crop coefficient (Kc) is commonly used as an indicator of plant responses to available water. Also, Kc is needed for estimating crop evapotranspiration (ETc), which represents the main route of water loss from both plant and soil surfaces and is a main component of water consumption in paddy field. Both Kc and ETc data are vital for irrigation scheduling and water resource allocation, management, and planning (Jensen et al. 1990). Commonly, Kc is derived empirically by using a lysimeter and is computed as the ratio of ETc to reference evapotranspiration (ETo) based on weather data. This method has been developed in Japan (Vu et al. 2005) and India (Tyagi et al. 2000; Mohan and Arumugam 1994) under FAO standard conditions with continuous flooding irrigation. However, this method is time consuming and expensive, especially for equipment preparation. In addition, no studies on Kc for SRI paddy under AWDI regime have been reported.

As explained in chapter 4, ETc could be estimated using linear program by Excel Solver method, thus Kc could also be determined by the estimation. In chapter 4 ETc was concluded to have been estimated quite properly. Therefore, Kc is also expected to be well estimated by this method.

The objectives of this chapter were to evaluate the estimated ETc by Excel Solver method and then to determine Kc for SRI paddy on daily basis using the estimated ETc. Then, the Kc value was compared to the Kc range of the FAO values under standard conditions.

5.2 Methodology

5.2.1 Data source for evaluation of the estimated crop evapotranspiration

We used the data in the third cropping season to evaluate estimated ETc by linear program with Excel Solver method. Here, the estimated ETc was determined according to the previous estimation in chapter 4. For the evaluation, the estimated ETc was compared to the ETc derived from the FAO procedure as a well established method (Allen et al. 1998). Indicators of model acceptance were same as in chapter 3, i.e., R^2 value, MSD and degree of significance (p value).

5.2.2 Crop coefficient

Based on the FAO recommendation (Allen et al. 1998), Kc value can be determined as a single Kc value or a dual Kc values. Dual Kc values consist of the soil evaporation coefficient and the basal crop coefficient to show the effects of soil evaporation and crop transpiration separately. Here, we used a single Kc value to examine the effect of both crop transpiration and soil evaporation simultaneously. Kc value was computed from the following equation:

$$Kc = \frac{ETc}{ETo} \qquad (19)$$

where ETo is reference evapotranspiration which was calculated based on Penman-Monteith model according meteorological data (Allen et al. 1998), and ETc is crop evapotranspiration. Here, Kc value was calculated on the daily basis and each value was filtered by using the Kalman filter equation (Welch and Bishop 2006; Kalman 1960) to show the trend. Average Kc value was then calculated for each growth stage, i.e., initial, crop development, mid-season, and late season stages. Finally, their values were compared to the Kc value ranges by the FAO.

5.3 Results and Discussion

5.3.1 Evaluation of estimated crop evapotranspiration

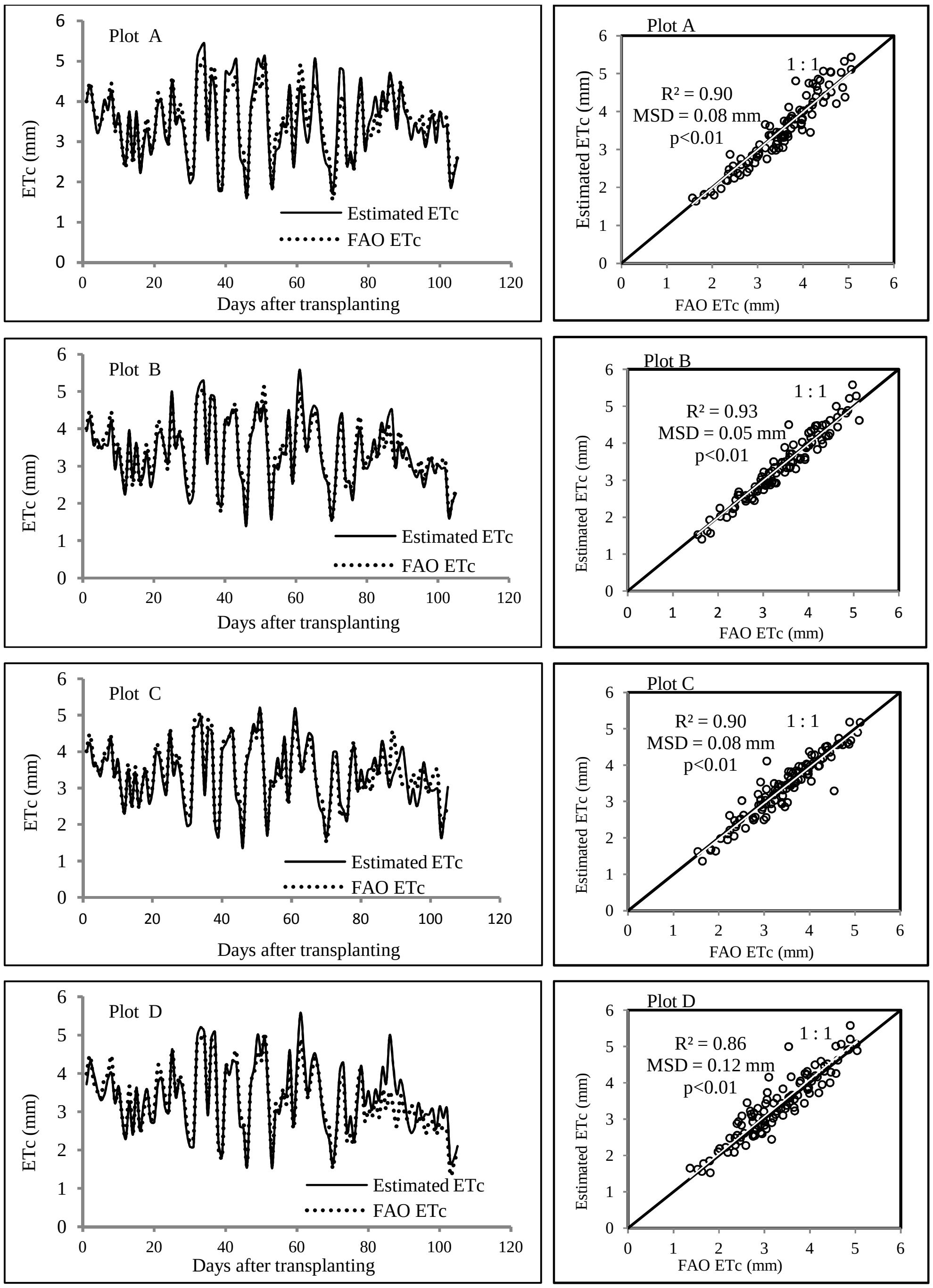


Figure 36. Correlation between the estimated ETc and the ETc by FAO procedure

Figure 36 shows correlations between values of estimated ETc and ETc by FAO procedure. The estimated ETc had high degrees of correlation to the FAO value for all regimes. R^2 values were greater than 0.85 ($p<0.01$) indicating that Excel Solver estimation was reliable when applied for ETc estimation under different irrigation regimes as suggested by Luo et al (2009). The result revealed that more than 85% the variability of ETc by the FAO procedure can be well estimated by the model, thus a tight correlation between estimated ETc and ETc by FAO procedure was observed. Also, MSD values were very low (<0.13 mm) revealed that deviation between estimated ETc and the FAO value was very small.

5.3.2 Estimation of crop coefficient

Changes in daily Kc value for SRI paddy were large throughout most of the cultivation period (Figures 37-40). The Kalman filter method smoothed the data and provided continuous lines during cultivation period for all regimes. During initial to mid-season growth stages, Kc value gradually increased and reached a peak in mid-season stage. Then, the Kc value declined rapidly in the late season stage as the soil moisture decreased. This trend was same for all plots as presented in Figures 37-40.

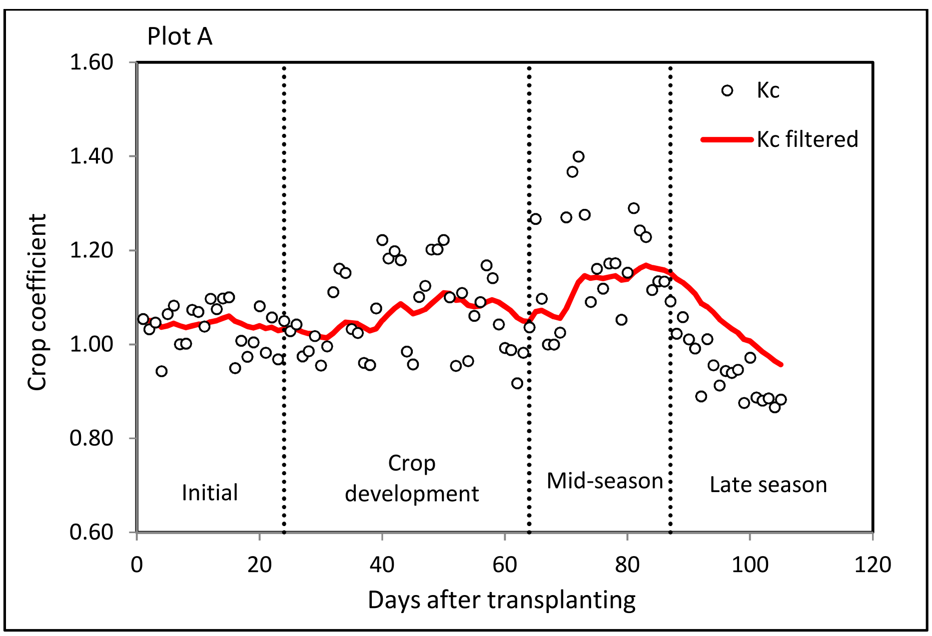


Figure 37. Daily Kc curve for water management regime in plot A

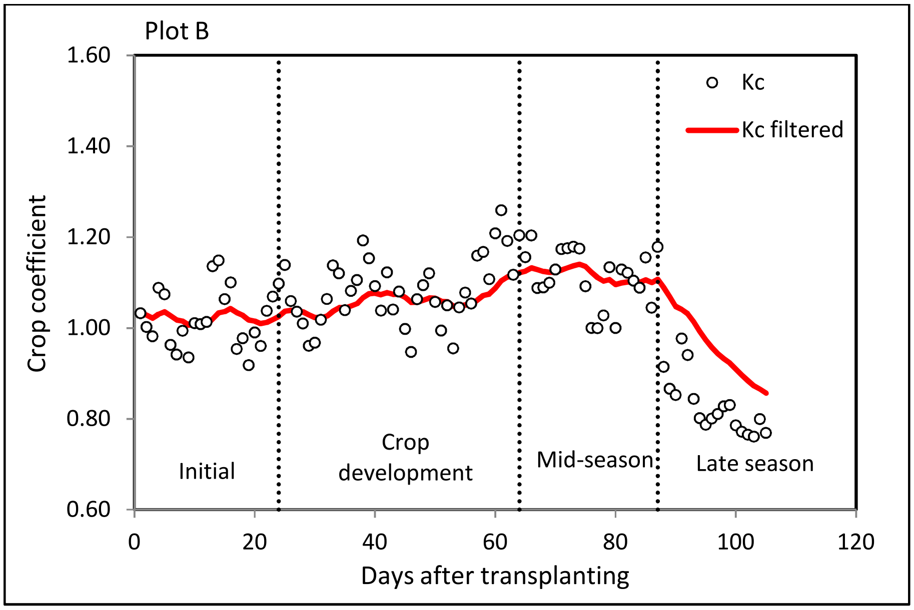


Figure 38. Daily Kc curve for water management regime in plot B

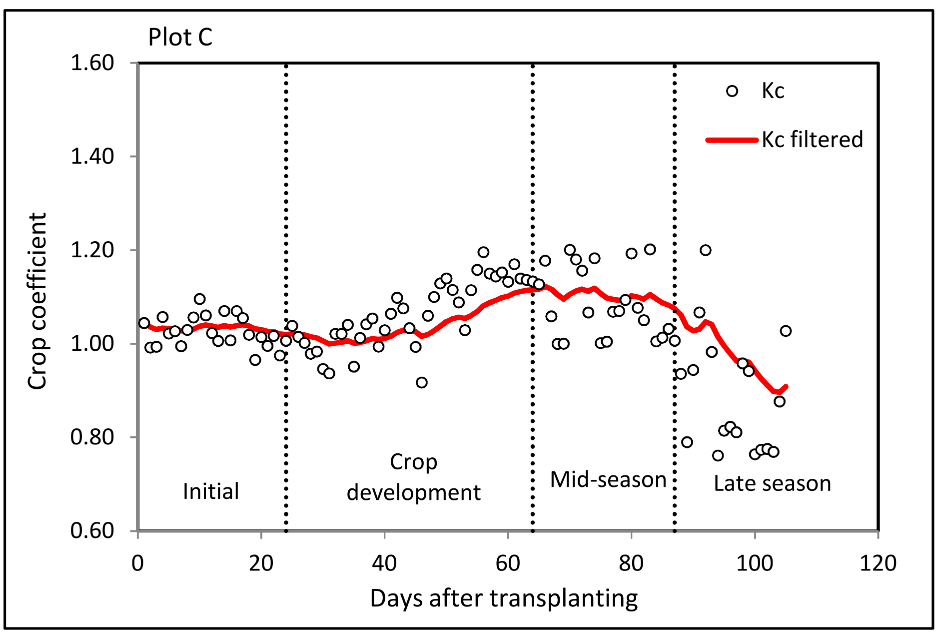


Figure 39. Daily Kc curve for water management regime in plot C

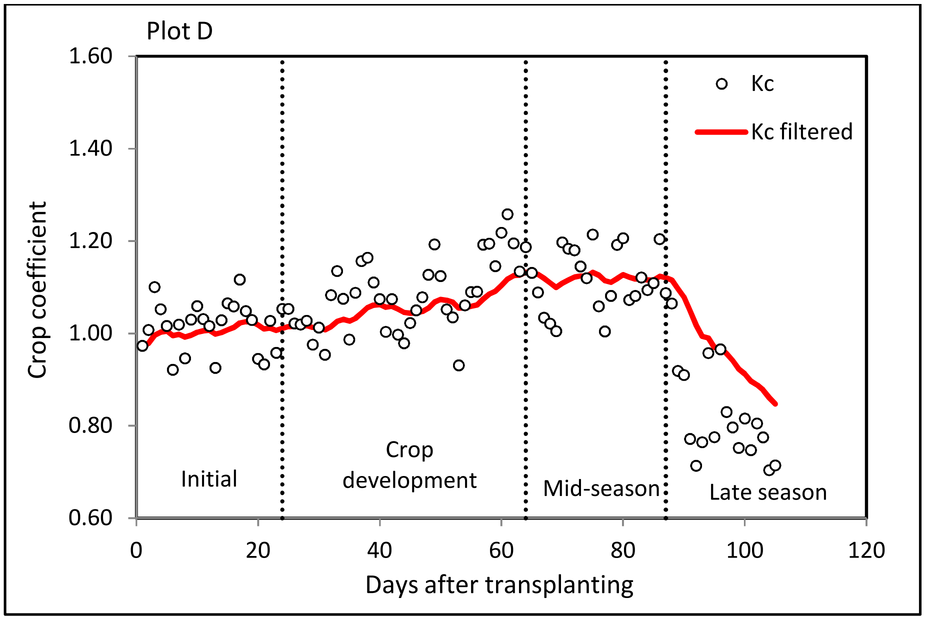


Figure 40. Daily Kc curve for water management regime in plot D

The increase in Kc value during initial to mid-season stage was due to rapid plant development from single seedlings until covering the entire fields. Then, during the late season stage, Kc value decreased until reaching the lowest value when the soil moisture reached its minimum value. This result indicated that Kc was affected by crop growth stage and available water in the field (Allen et al. 1998).

Table 8. Average Kc value in each growth stage

Growth stage	Kc value each plot				
	Plot A	Plot B	Plot C	Plot D	FAO Kc range
Initial	1.04	1.02	1.03	1.00	1.10-1.15
Crop development	1.06	1.06	1.04	1.06	1.10-1.15
Mid-season	1.13	1.12	1.10	1.12	1.10-1.30
Late season	1.04	0.96	0.98	0.97	0.95-1.05

Table 8 records average Kc values for SRI paddy under AWDI regimes in the third cropping season compared to the typical ranges reported by the FAO for rice cultivation under the standard conditions (Doorenbos and Kassam 1979). In the initial stage, Kc values for all regimes were lower than those for the FAO standard condition. The lower Kc values in the SRI paddy field were caused by the application of non-flooding irrigation in which the actual field conditions were drier than that for the FAO standard conditions. In addition, single transplanting with younger seedlings in SRI paddy field resulted in the lower transpiration rate because at this stage water consumption is directly proportional to transpiration (Heinemann et al. 2011).

In the crop development stage, Kc values for the SRI paddy increased because of the plant activity for vegetative development (root, stem, leaf and tiller). However, the values were also lower than those for the FAO standard condition because the SRI field was drier than the standard conditions. Therefore, soil evaporation was lower than that for the standard conditions in this stage.

In the mid-season and late season stages, the average Kc values were within the range of the FAO, though the water input was lower than that of the FAO standard. This result indicated that AWDI promoted more plant activity by providing optimal water and oxygen availability (Yang and Zhang 2010). Therefore, a greater number of tillers/hill was developed for dry biomass production.

5.4 Conclusions

The estimated crop evapotranspiration (ETc) had a high degree of correlation to the ETc derived from the FAO procedure. Therefore, Excel Solver was reliable to estimate ETc under AWDI regimes. By using the estimated ETc, crop coefficient (Kc) can be well determined with a reasonable trend during cultivation period. Kc value increased gradually in the initial and crop development stages, and it reached a peak in the mid-season stage. Then, Kc value declined rapidly in the late season stage. The average Kc values for SRI paddy was lower than the Kc ranges suggested by FAO under standard conditions in the initial and crop development stages. Then, the average Kc values were within the range of the FAO for the mid-season and late season stages even though the soil moisture level decreased.

Chapter 6: Optimizing SRI Water Management using Genetic Algorithm

6.1 Background

The optimal wet and dry levels (represented by soil moisture) for each growth stage are still unclear because there is a lack of information on studies of optimizing water management in SRI paddy field. Thus, this chapter was undertaken to find the optimal soil moisture levels during cultivation period to maximize yield and water productivity.

In the irrigation planning model, there are many factors to be considered, such as crop water requirement, production function of irrigation water, precipitation, soil water balance including irrigation water, plant growth stage, etc (Zhang et al. 2008). It is difficult problem to find the optimal or near optimal solution with traditional optimization methods because the limitations in integrating of multi-factors in the model. Thus, genetic algorithm (GA) proposes global optimization search with many remarkable characteristics by searching the entire population instead of moving from one point to the next as the traditional methods (Kuo et al. 2000).

GA has the ability to rapidly search a global optimal value of a complex objective function using a multi-point search procedure involving crossover and mutation processes (Goldberg 1989). GA differs from the traditional optimization and other search methods in the following ways: (1) GA works with a coding of the parameter set, not the parameters themselves, (2) GA searches from population of points, not a single point, (3) GA uses objective function, not derivatives or other auxiliary knowledge, and (4) GA uses probabilistic transition rules, not deterministic rules (Goldberg 1989). GA has been applied to several irrigation planning applications (Zhang et al. 2008; Wardlaw and Bhaktikul 2004; Raju and Kumar 2004; Kuo et al. 2000). However, optimizing AWDI in any SRI paddy fields have not yet been achieved by finding the optimal soil moisture in each growth stage.

Therefore, the main objectives of this chapter were to identify effects of irrigation regimes on yield and water productivity and then to find the optimal water management by determining optimal combination of soil moisture levels using GA with the purpose to maximize yield and water productivity simultaneously.

6.2 Methodology

6.2.1 Field data for analyzing and optimizing

The identification and optimization processes were carried out based on the results of the field experiment in NOSC, Sukabumi, West Java, Indonesia. All data consisting of soil moisture and meteorological parameters were collected by the FMS prior to three cropping seasons.

As explained previously, there were four plots in each season with different regimes represented by different soil moisture levels. For plant parameters, observations were taken at regular intervals for vegetative and reproductive parameters. Several key parameters like plant height, tillers/hill and yield were used to assess the regime effects on plant growth and performance. Each plot was divided into five parts and a single hill in each part was selected to determine plant height and tillers/hill.

6.2.2 Modeling Approach

Identification procedure

To find the optimal irrigation regime to maximize yield and water productivity, the effect on irrigation regimes on yield and water productivity should be identified firstly based on empirical data. There were 12 different irrigation regimes with different levels of soil moisture in each growth stage. The regimes resulted in different yield and water productivity. Since there was no mathematical model between soil moisture levels, yield and water productivity, the identification process was carried out gradually following procedures as below:

1. Yield as a function of plant height and tillers/hill

The yield has a positive correlation to plant growth represented by plant height and tillers/hill. Therefore, we used multiple linear regression analysis to show the correlations between the yield and plant height as well as tillers/hill. The basic formula was given as:

$$Y = aPH + bTH + c \qquad (20)$$

where Y is yield (ton/ha), PH is plant height (cm), TH is tillers/hill, a and b are coefficient for plant height and tillers/hill, c is constant. Plant height and tillers/hill were measured manually every 5 days and we used their average values in the end of mid-season stage when maturity time started to show their correlation to the yield (Allen et al. 1998). Here, all coefficient and constant in equation 20 were determined empirically according to the field experiment data by performing multiple linear regression analysis.

2. Plant height and tillers/hill as a function of soil moisture

Plant height and tillers/hill are affected by soil moisture level in each growth stage. In fact, it is difficult to identify the relationship between soil moisture and plant growth by developing mathematical model. Thus, we implemented the NN model to show the correlation since the NN model deals with complex systems such as agricultural systems (Hashimoto 1997). The model consisted of three layers, i.e., input, hidden, and output layers. Soil moisture in the initial (SM1), crop development (SM2), mid-season (SM3) and late season (SM4) stages were used as in the input, while plant height (PH) and tillers/hill (TH) as the output (Figure 41). Indicators of model acceptance were same as in chapters 3 and 5, i.e., R^2 value, MSD and degree of significance (p value).

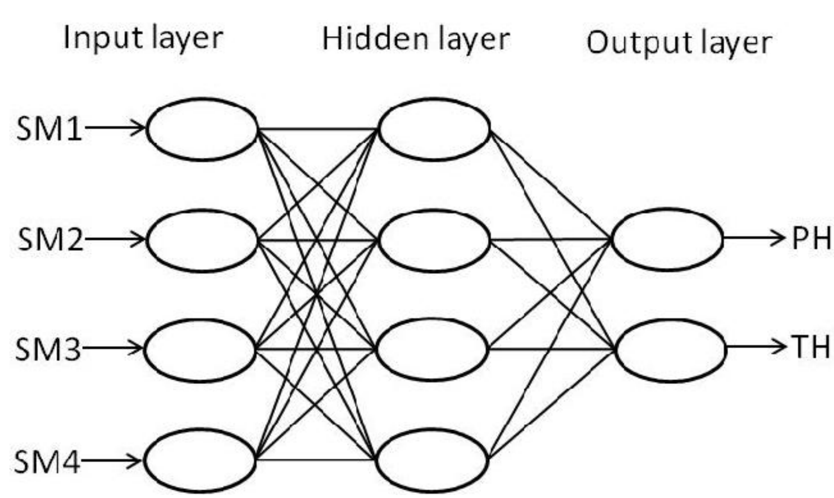


Figure 41. Structure of NN model to identify plant height and tillers/hill as function of soil moisture

3. Water productivity with respect to total water input

Since we focused on finding the minimum water input as much as possible, we defined water productivity with respect to the total water input (Bouman et al. 2005) with the following equation:

$$\mathrm{WP} = \frac{\mathrm{Y}}{\sum(\mathrm{I}+\mathrm{P})} \qquad (21)$$

where I is estimated irrigation water (mm) affected by the soil moisture level in each growth stage, P is precipitation (mm), and WP is water productivity (g grain/kg water).

Optimization procedure

The objective function was:

$$\mathrm{F(SM1,SM2,SM2,SM4)} = \mathrm{dY} + \mathrm{eWP} \qquad (22)$$

Maximize F(SM1,SM2,SM3,SM4)

Subject to:

$$0.586 \le \mathrm{SM1} \le 0.622\ (\mathrm{cm}^3/\mathrm{cm}^3) \qquad (23)$$

$$0.563 \le \mathrm{SM2} \le 0.593\ (\mathrm{cm}^3/\mathrm{cm}^3) \qquad (24)$$

$$0.455 \le \mathrm{SM3} \le 0.522\ (\mathrm{cm}^3/\mathrm{cm}^3) \qquad (25)$$

$$0.350 \le \mathrm{SM4} \le 0.505\ (\mathrm{cm}^3/\mathrm{cm}^3) \qquad (26)$$

where d and e are weights for the yield (Y) and water productivity (WP) and their values were 0.6 and 0.4, respectively. Since both Y and WP have different units, their values were normalized using their maximum and minimum values based on empirical data. Here, GA model searched the optimal combinations of SM1, SM2, SM3, and SM4 with their ranges between minimum and maximum soil moisture in each growth stage according to experimental data to maximize the objective function by the multi-point searching procedure.

In order to employ a GA model, some parameters such as individual, population, fitness function, and operators of GA should be defined previously as follows:

1. Definition of individual

An individual represented a candidate for the optimal solution that consisted of particular values of SM1, SM2, SM3 and SM4. Meanwhile a set individual was called population. An individual was coded as a set of six-bit binary strings as illustrated in Figure 42.

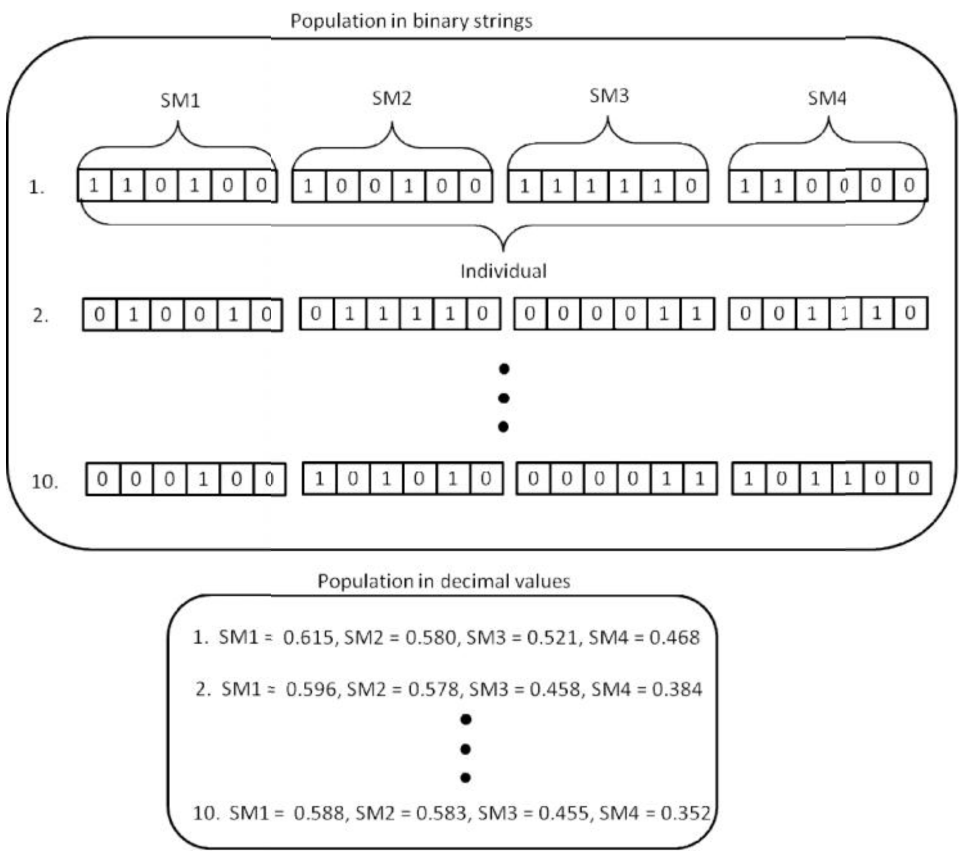


Figure 42. Some individuals in a population of GA model

2. Fitness function

Fitness function is an indicator to show the quality of an individual. All individuals in a population were evaluated based on their performances in which the higher fitness function, the better ability to survive. In this problem, fitness function was the same as the objective function

3. Operators of GA model

The main operators were crossover and mutation. Crossover combined features from two individuals based on crossover rate. It is operated by swapping corresponding component in the binary strings representing an individual. Mutation inverted one or more bit binary string (also called gene) in each individual from 0 to 1 or 1 to 0 based on mutation rate. Here, the rates were 60% and 5% for crossover and mutation, respectively.

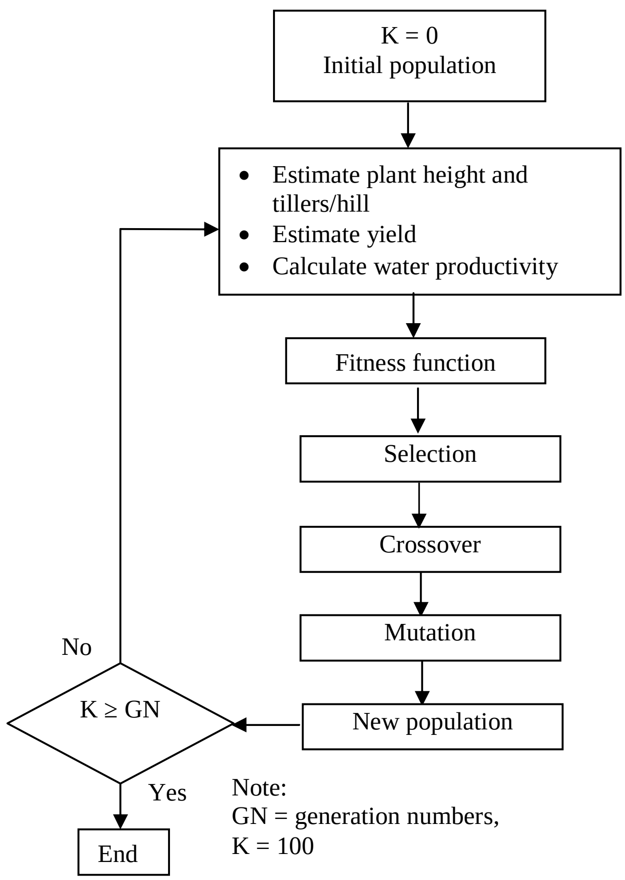


Figure 43. Searching procedure of GA model in this study

We adopted the searching procedure developed previously (Suhardiyanto et al. 2009) based on Figure 43, and here, the detail can be referred to Appendix 6 with the explanation as follows:

1. An initial population consisting of ten individuals were generated randomly as the first generation
2. Based on each individual, yield was estimated using equation 20. Then, water productivity was calculated using equation 21
3. Fitness of each individual was calculated to show the performance
4. The performance of each individual was evaluated by sorting the maximum to the minimum fitness value. Here, as the best performers, 60% of all individuals were qualified for the next step, while the others were eliminated
5. Crossover and mutation operations were applied to the selected individuals based on crossover and mutation rates
6. Then, a new population was created. Here, 60% of the selected individuals in the previous selection were compared with the new individuals in creating new population. We implemented the elitist strategy to find the global optimum by sorting the fitness values and then selected top ten individuals with the best performance to be a new population as the next generation.
7. Steps 2 to 6 were repeated until the 100^{th} generation. The individual with the optimal genotype was revealed the highest fitness.

We developed a GA model in Microsoft Excel 2007 with Visual Basic using our own codes. Details of GA model source code in Visual Basic language can be seen in Appendix 5.

6.3 Results and Discussion

6.3.1 Effects of irrigation regimes on yield

Table 9 summarizes the climatic data during the experiments in three seasons. There are two seasons in Indonesia classified based the pattern of precipitation. Here, precipitation among seasons was quite different in which the highest intensity occurred in the first season with total precipitation of 1332 mm in rainy season. Consequently, different pattern in precipitation corresponded to the different pattern of solar radiation as well as reference evapotranspiration. The lowest solar radiation and reference evapotranspiration occurred in the first season with total values of 1464 MJ/m^2/season and 311 mm, respectively. Meanwhile, temperatures among the seasons were quite same in which maximum temperature was 32.8^{o}C and minimum temperature was 16.2^{o}C in the second season.

Table 9. Meteorological data during experiments

Seasons	Precipitation (mm)	Temperature (^{o}C)			Solar radiation (MJ/m^2/season)	ETo (mm)
		Minimum	Average	Maximum		
I (Rainy)	1332	19.5	23.5	31.9	1464	311
II (Dry-Rainy)	626	16.2	24.0	32.8	1827	429
III (Rainy-Dry)	551	17.4	24.3	32.3	1652	345

As discusses in chapter 2 that actual water level could not be controlled well by the irrigation control system, thus the water levels were different among plots. Therefore, irrigation regimes were eventually different among the plots and the cropping seasons. During three cropping seasons, there were 12 different irrigation regimes with different soil moisture as shown in Figure 44.

In the first to the middle cultivation period (initial and crop development stages), soil moisture level in the first and second seasons were lower than that in the third season. In these stages, soil moisture levels were in between saturated and field capacity in the first and second periods. Meanwhile, in the third season soil moisture level was in saturated border indicated that during period the field was wetter than that in the first and second period for all plots.

In the mid-season stage, soil moisture levels among seasons were in between saturated and field capacity borders for all plots. Finally, in the last season stage, the contrary condition was occurred between the third and the first seasons as well as the second season. Here, in the third season the field was drier than that in the first and second seasons for all plots.

The patterns of soil moisture levels are important to identify effect of irrigation regimes on the yield and crop performances. Although the climatic conditions are also important as factors in obtaining yield, but they are uncontrolled parameters. Thus, we only consider controlled parameter i.e., soil moisture level in obtaining optimum yield.

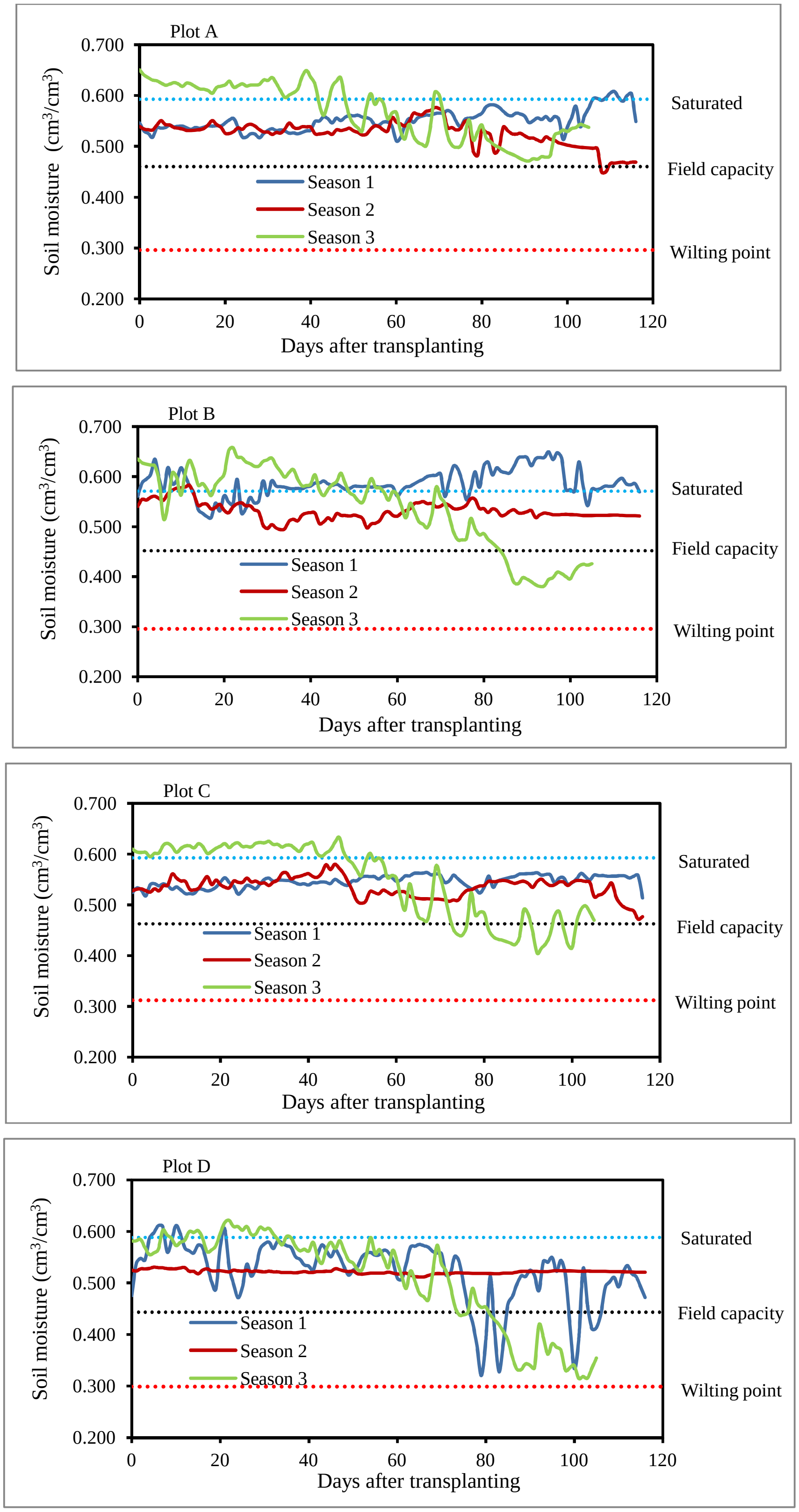


Figure 44. Changes in soil moisture during cultivation period for each plot

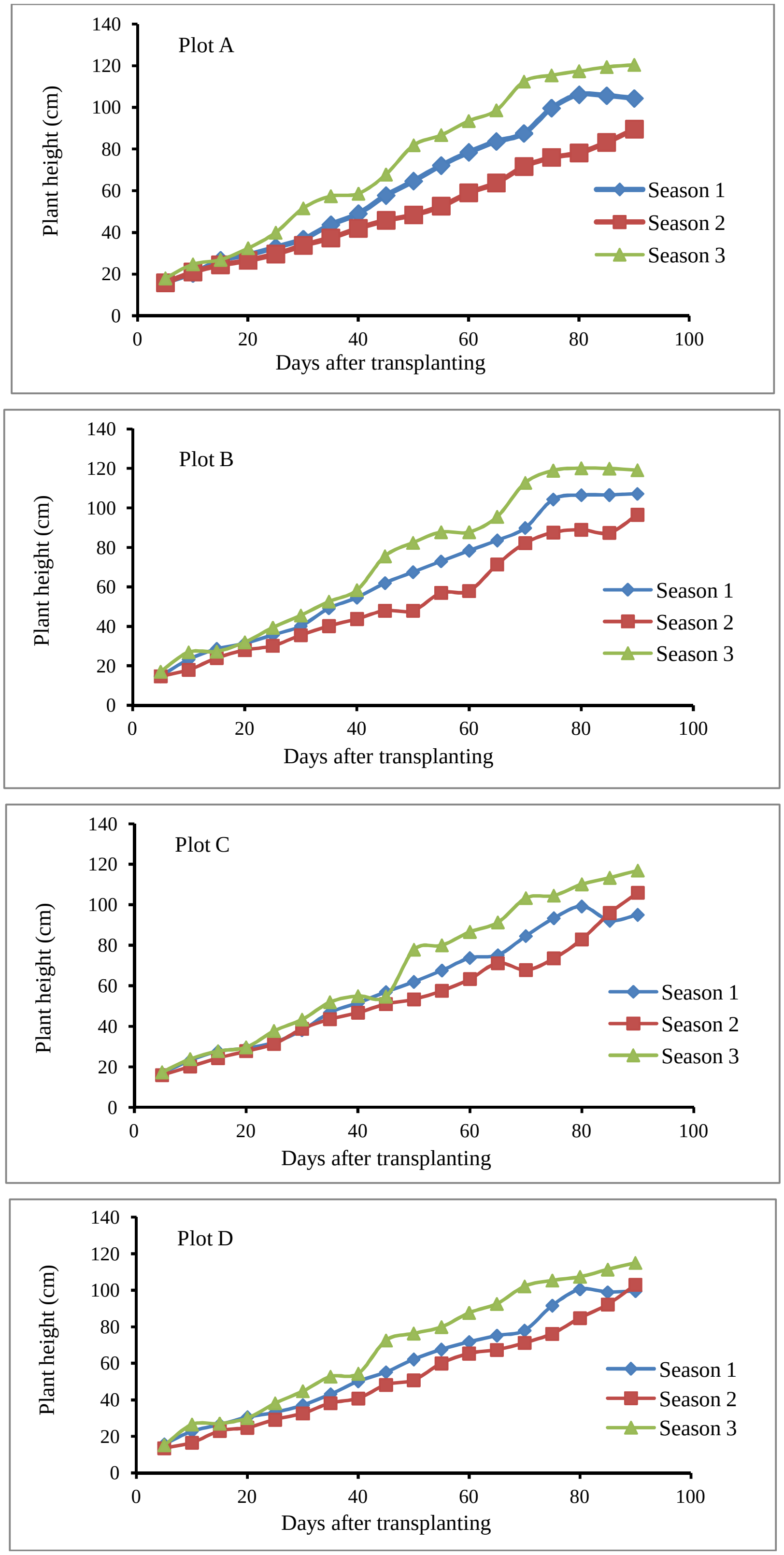


Figure 45. Plant height during cultivation period for all plots in each season

Figure 45 shows the plant height during cultivation period in all plots among the seasons. In the initial and crop development stages, the plant height was comparable among the seasons. However, starting from the mid-season stage, the plant grew faster particularly in the third season for all plots indicated the highest plant height was obtained in this season. These results revealed that suitable field conditions occurred for plant grew optimally in the third season when soil moisture levels in between saturated and field capacity borders in the mid-season stage and then to be drier in the late season stage.

Figure 46 shows linear correlation between the average soil moisture in each growth stage and the yield. The third season obtained the highest yield compared to other seasons. The average yield was 4.77, 4.23 and 9.38 ton/ha for the first, second and third seasons, respectively. Hence, soil moisture levels have correlation to the yield for all growth stages.

In the initial and crop development stages, soil moisture had positive correlation to yield with an R^2 of higher than 0.6. This result revealed that at higher soil moisture levels, more yield was produced. In the initial stage, the maximum yield was produced when the soil moisture level was over the saturation border indicating shallow standing water was occurred in the field. Commonly, Indonesian farmers call this condition as *macak-macak* in the Indonesian language. Then, in the crop development stage, the maximum yield was achieved when the soil moisture level was close to the saturation border. The field condition in the crop development stage was drier than that in the initial stage, even though both conditions were classified as wet condition.

On the contrary, soil moisture had negative correlation to yield in the mid-season and late season stages. Based on the empirical data, the mid-season stage was probably the transition in which the water can be drained to produce more yields. Here, the maximum yield was obtained when the soil moisture level was higher than the field capacity border (Figure 46). This revealed that the medium level was appropriate to produce more yields by draining water in the mid-season stage. Then, in the late season stage, the driest condition can be applied to save more water without a loss of significant yield.

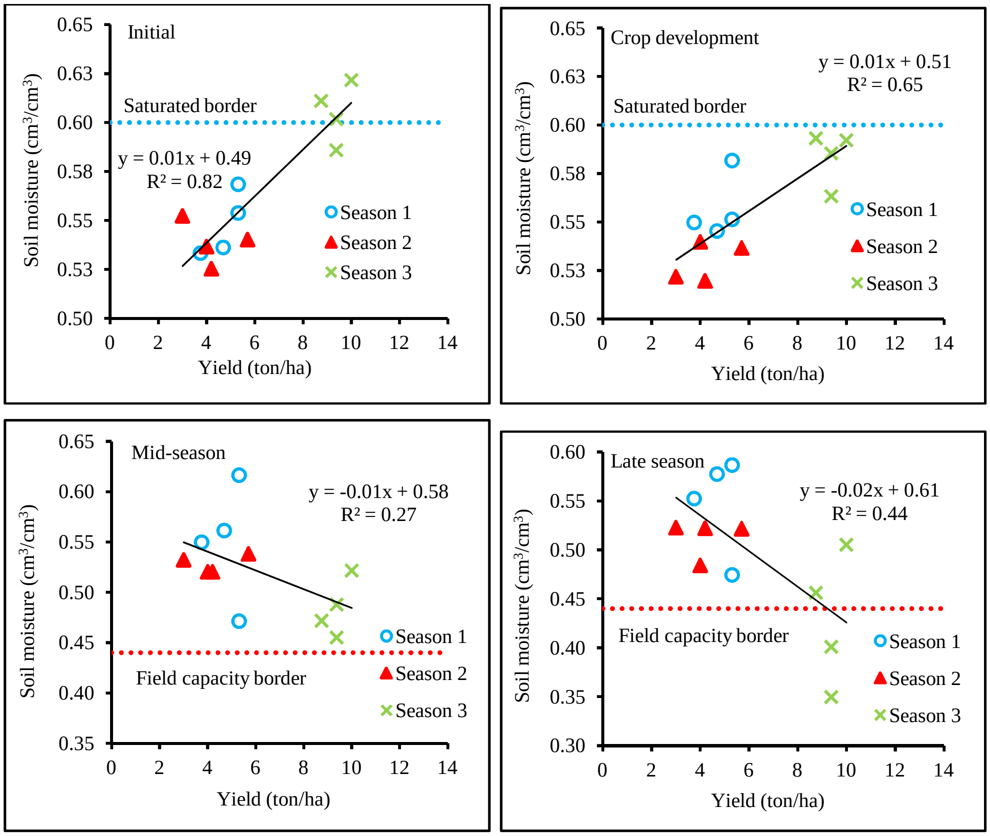


Figure 46. Linear correlation between the average soil moisture and the yield in each growth stage

6.3.2 Correlation between yield and plant growth or soil moisture

Based on empirical data, it was clearly observed that both plant height and tillers/hill have positive correlations to yield with R^2 of 0.86 and 0.89, respectively (Figure 47). The results were consistent with the previous findings that a higher plant height with more tillers/hill promoted more yields and *vice versa* (Kumar et al. 2012; Zeng et al. 2003). Therefore, the correlations between yield and both plant height and tillers/hill can be presented well by multiple linear regressions with an R^2 value of 0.94 (Figure 48). From this analysis, we found that values of a, b and c were 0.11, 0.32 and 13.03, respectively. Commonly, the yield of rice is highly dependent upon fertile tillers/hill, thus more tillers/hill have high probability to produce more fertile tiller (Zeng et al. 2003).

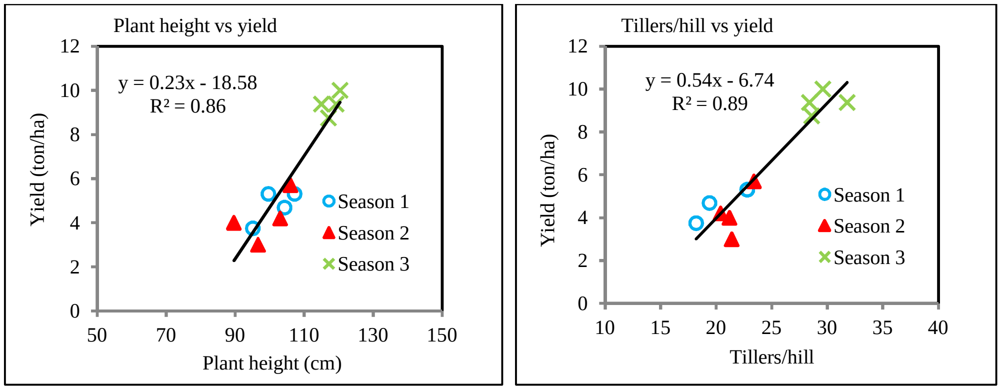


Figure 47. Correlation between plant height and yield, tillers/hill and yield

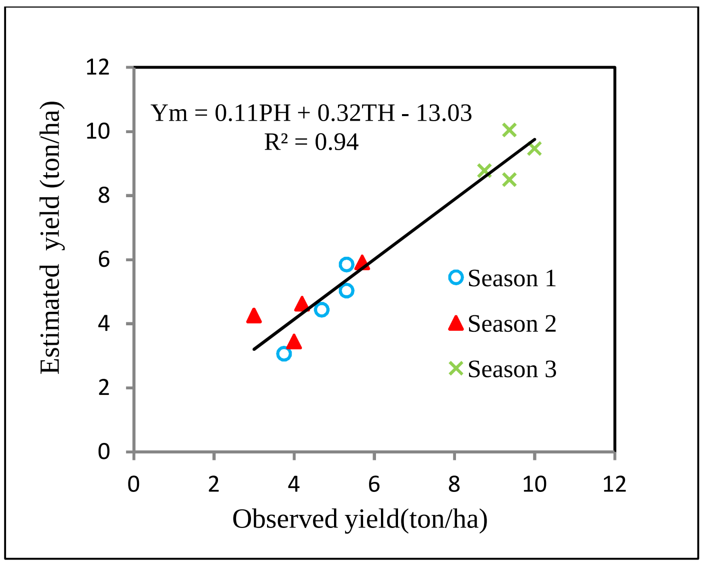


Figure 48. Multiple linear regression for describing plant height and tillers/hill by yield

Yield has also a positive correlation to crop evapotranspiration (ETc) with R^2 value of 0.39, 0.69 and 0.70 for the first, second and third seasons as presented in Figure 49. This result indicated that higher ETc promoted more evaporation from the soil and transpiration from the plant, thus greater yields were obtained as well as biomass production (Shih 1987). The linear correlation between ETc and yield is not only found for paddy rice (Shih et al. 1983), but also other crops such as corn (Ko and Piccinni 2009), cotton and wheat (Jalota et al. 2006). Therefore, ETc is usually used to estimate their yields (Shih 1987).

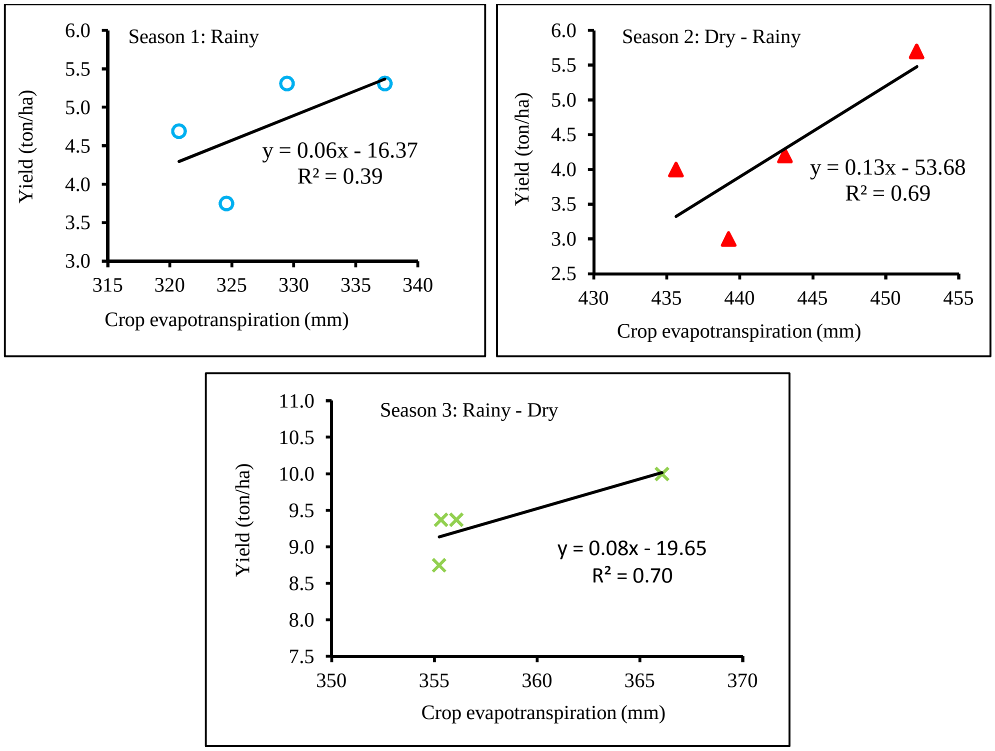


Figure 49. Correlation between yield and crop evapotranspiration in each season

ETc is vital for irrigation scheduling and water resource allocation, management, and planning (Jensen et al. 1990). We should consider weather conditions to determine ETc appropriately because different weather condition associated on the different ETc as presented in Figure 49. Also, since it is a main component of water consumption in paddy field, thus its rate depends on water availability in the field represented by soil moisture. In other words, plant growth and the yield were clearly affected by soil moisture level in each growth stage (Anbumozhi et al. 1998). However, there is no mathematical model that shows the relationship between soil moisture level and plant growth in each growth stage.

Here, we used the NN model to estimate plant growth represented by plant height and tillers/hill as affected by soil moisture level in each growth stage. Figure 50 shows the comparisons between observed and estimated values of both plant height and tillers/hill by the NN model. It can be seen that the estimated values were closely related to the observed values with R^2 value of 0.77 and 0.92 ($p < 0.01$) and MSD of 16.92 cm and 1.38 for estimation of plant height and tillers/hill, respectively. This means that more than 75% of the variability of observed values can be predicted by the NN model. Therefore, the results suggest that a reliable simulation model by the NN model could be obtained to estimate plant height and tillers/hill.

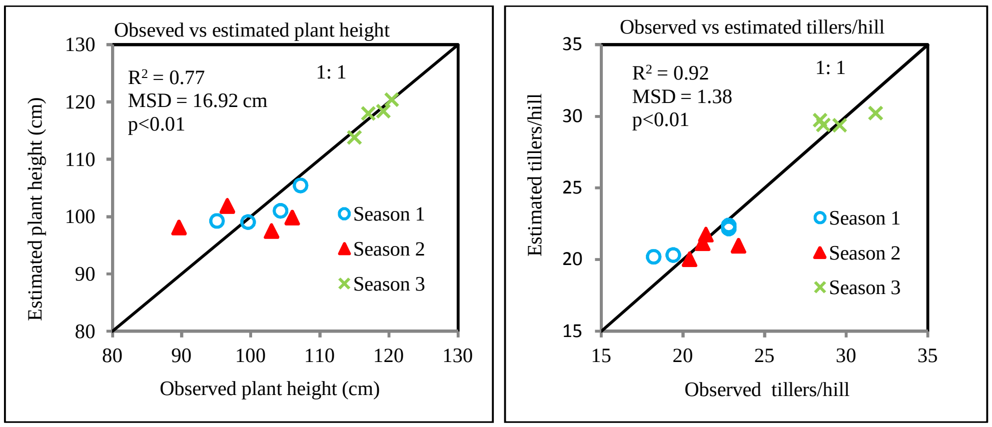


Figure 50. Observed and estimated plant growth affected by soil moisture level estimated by the NN model

6.3.3 Optimal soil moisture levels by Genetic Algorithm

Figure 51 shows the evolution curves of fitness values between their maximum, average and minimum values in each generation. All values increased sharply from the first to the tenth generation, and then increased gradually until the 40th generation. After the 40th generation, the all fitness values were convergent until the end of generation and their values were 0.68. This means that the global maximum value was obtained because all of their maximum, average and minimum values were the same.

Figure 52 shows the evolution curves of soil moisture level in each growth stage in obtaining fitness values presented in Figure 51. SM1 and SM2 converged faster than the other growth stages; their values reached the asymptote before the tenth generation. Meanwhile, SM3 became convergent most slowly; in the 40th generation, at which the fitness value was also starting to be convergent (Figure 52). This means that the optimal soil moisture level in each growth stage that maximizes the yield and water productivity was obtained from the model simulation based on the GA procedure after the 40th generation.

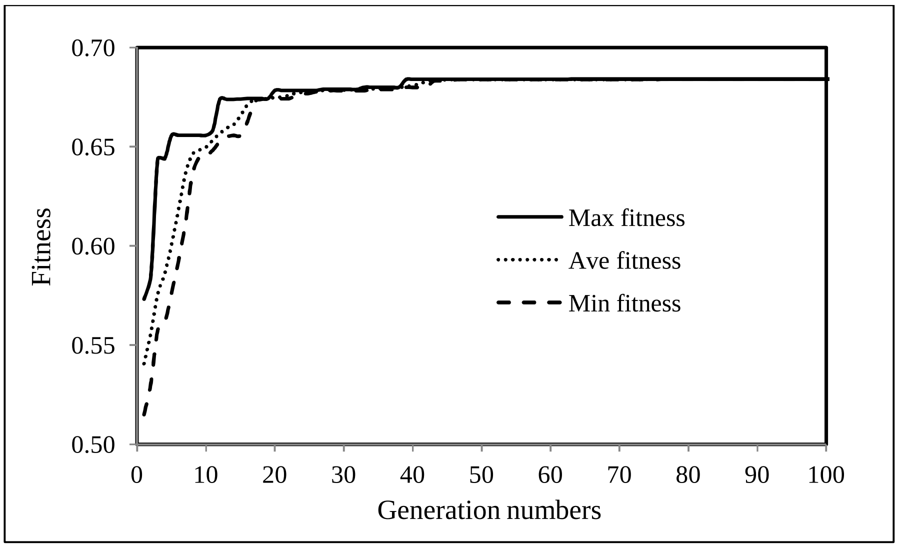


Figure 51. Evolution curves in searching for a maximal value of fitness function

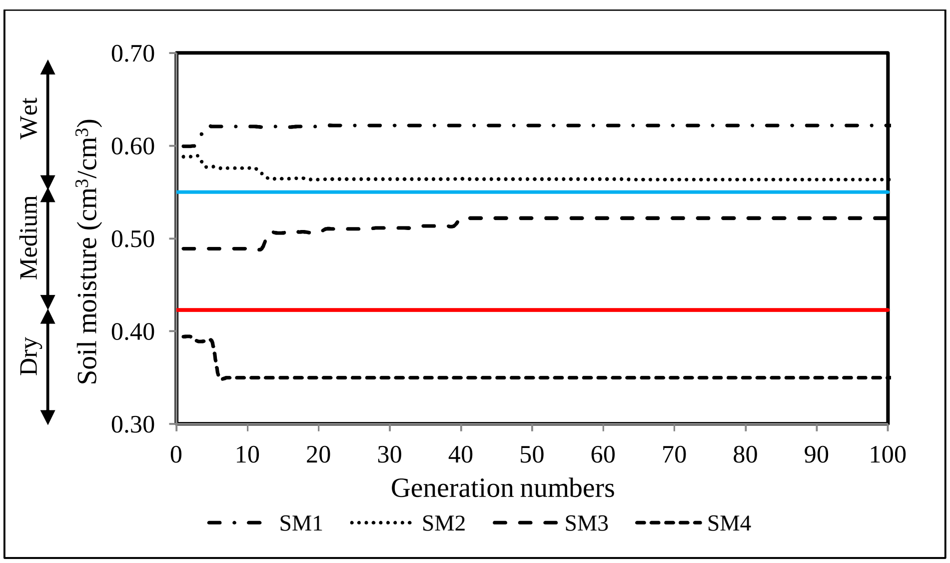


Figure 52. Evolution curves in searching the optimal values of soil moisture in each growth stage

Table 10 shows the optimal soil moisture level in each growth stage obtained by the GA model, while Figure 53 shows the optimal output simulated by the GA model. Four irrigation regimes with the combinations of soil moisture levels from the field measurements are also represented in the table with the same precipitation during the third cropping season as the comparison. The optimal combination of soil moisture levels in the growth stages obtained in this chapter was 0.622 (wet), 0.563 (wet), 0.522 (medium), and 0.350 cm^3/cm^3 (dry) for SM1, SM2, SM3 and SM4, respectively. By this scenario, it was simulated that the yield can be increased up to 6.33% and water productivity up to 25.09% with water saving up to 12.71%.

Table 10. Optimal soil moisture level in each growth stage and its comparison to the irrigation regimes in the third cropping season

Components	Irrigation regimes				GA model	
	Plot A	Plot B	Plot C	Plot D	Optimal Regime	Level
Soil moisture (cm^3/cm^3)						
Initial (SM1)	0.622	0.602	0.611	0.586	0.622	Wet
Crop development (SM2)	0.592	0.585	0.593	0.563	0.563	Wet
Mid-season (SM3)	0.522	0.488	0.472	0.455	0.522	Medium
Late season (SM4)	0.505	0.401	0.456	0.350	0.350	Dry
Yield (ton/ha)	10.00	9.38	8.75	9.38	10.63	
Total irrigation (mm)	343	295	305	272	299	
Total precipitation (mm)	551	551	551	551	551	
Water productivity (g grain/ kg water)	1.12	1.11	1.02	1.14	1.25	
Water saving (%)	-	13.86%	11.01%	20.65%	12.71%	

From this simulation, it was shown that during the first and second stages keeping the field in the wet level is important to fulfill the plant water requirement for vegetative development. This result was supported by the empirical data that the maximum yield was obtained when a wet level was developed in the field. In SRI paddy field, to avoid continuous flooding is one of the elements because rice plants cannot grow best under limited oxygen in the soil, thus plants should be given just enough water at saturated condition (or *macak-macak* condition) to meet their requirement for root, stem and tiller development (Uphoff et al. 2011).

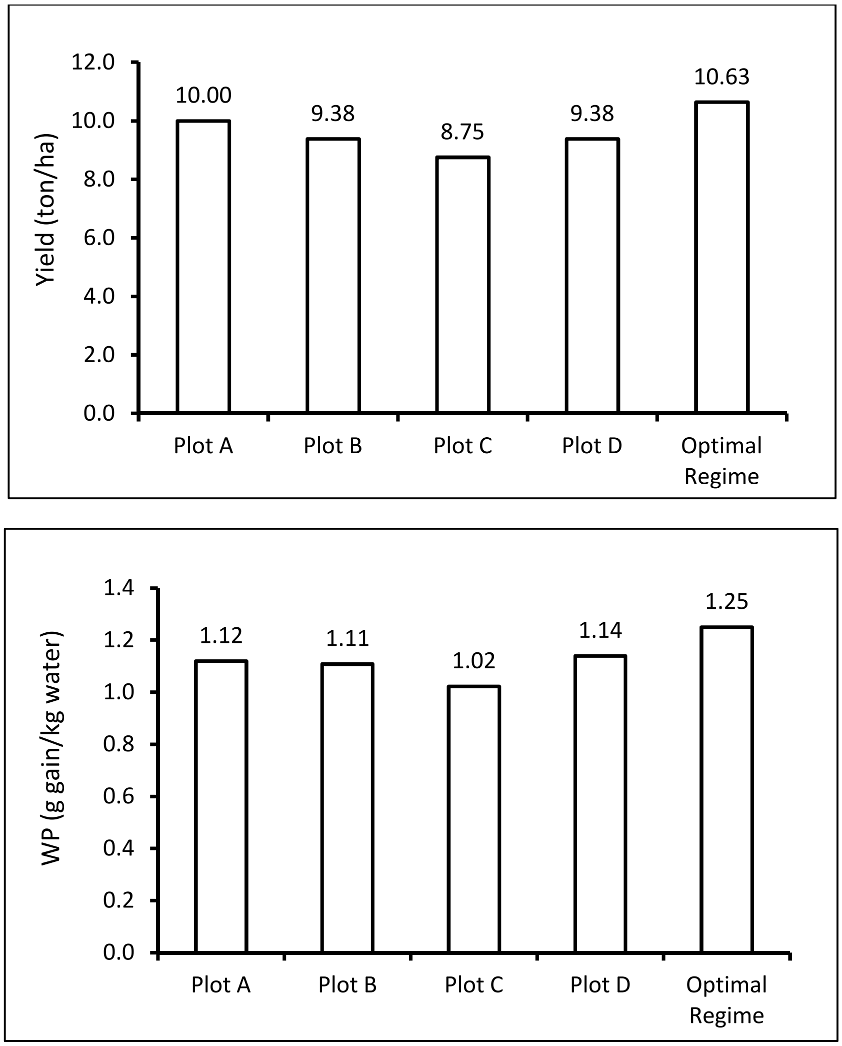


Figure 53. Optimal the yield and water productivity estimated by the GA model and their comparison to the empirical data

Then, the field can be drained into the medium level in the third stage when the plants focusing on the reproductive stage (flowering and panicle development). The medium level is important in developing aerobic condition to avoid spikelet sterility particularly around the flowering time (Bouman et al. 2005). Finally, the field should be drained into dry level in the last stage to save water as reported in the previous studies (Uphoff et al. 2011; Doorenbos and Kassam 1979; Zawawi et al. 2010). This recommendation was also supported by the empirical data that medium and dry levels in the mid-season and late season stages resulted in the maximum yield.

6.4 Conclusions

In this chapter, the optimal combination of soil moisture levels was estimated by the GA model for the growth stages to maximize both the yield and the water productivity of the SRI paddy field. The simulation was performed based on the identification process using the empirical data during the three cropping seasons. As a result of the simulation, the optimal values were estimated at 0.622 (wet), 0.563 (wet), 0.522 (medium), and 0.350 cm^3/cm^3 (dry) for the initial, crop development, mid-season, and late season growth stages, respectively. The wet level in the initial and crop development growth stages should be achieved to provide enough water for vegetative development, and then the field can be drained with the irrigation threshold of field capacity to avoid spikelet sterility in the mid-season stage and finally, to complete the production, it is important to let the field dry to save more water in the late season stage. By this scenario, it was estimated that the yield can be increased up to 6.33% and water productivity up to 25.09% with water saving up to 12.71%.

Chapter 7: Effects of Water Management on Greenhouse Gas Emissions from SRI paddy field

7.1 Background

In the conventional rice cultivation, continuous flooding irrigation is applied during the cultivation period by maintaining the depth of water between 2 and 5 cm. Thus, oxygen and sulfate are scarce in that soil environment. This condition enhances methanogenesis through organic matter decomposition (Bouwman 1990). The increase of methane concentration in the atmosphere contributes to global warming (Ramanathan et al. 1985). Therefore, the conventional paddy field is known as a major source of greenhouse gases particularly methane (Cicerone et al. 1992; Neue et al. 1990).

Moreover, paddy fields are also known as a source of other greenhouse gases such as nitrous oxide. Although an early study found nitrous oxide emission from the paddy fields to be negligible (Smith et al. 1982), however, later studies suggested that paddy fields are an important source not only of methane but also of nitrous oxide (Cai et al. 1997). Nitrous oxide is primarily produced from microbial processes, nitrification and denitrification in soil (Mosier et al. 1996).

Methane emission has a negative correlation to nitrous oxide (Cai et al. 1997). The nitrous oxide emission is very small when the paddy field is flooded, but nitrous oxide increases at the beginning of the disappearance of floodwater. Moreover, its emission increased dramatically when fertilizer N was induced to the field (Snyder et al. 2007; Akiyama et al. 2005). In contrast, nitrous oxide emission increased during flooding and was significantly reduced by water drainage (Setyanto et al. 2000). Therefore, water management regime is one of the most important tools in rice production and is the most promising option for methane and nitrous oxide mitigation (Tyagi et al. 2010; Akiyama et al. 2005).

Many researchers have conducted the experiments to find the optimal water management for mitigating the net global warming potential (GWP) of paddy field. They found that mid-season drainage irrigation was an effective option to reduce the net GWP (Towprayoon et al. 2005; Akiyama et al. 2005). However, those experiments were conducted under conventional rice production. The number of studies on effects of water management on greenhouse gas emissions in SRI paddy field is limited.

Therefore, the main objectives of this chapter were to investigate effects of water management on greenhouse gas emissions in SRI paddy field, and to select the best mitigation strategy among the regimes

7.2 Methodology

7.2.1 Field experiments

The field experiment was conducted in the greenhouse of Meiji University, Kanagawa Prefecture, Japan from 4 June to 21 September 2012. The greenhouse is located at 35°36'39.67"N and 139°32'52.38"E, at an altitude of 76 m above mean sea level.

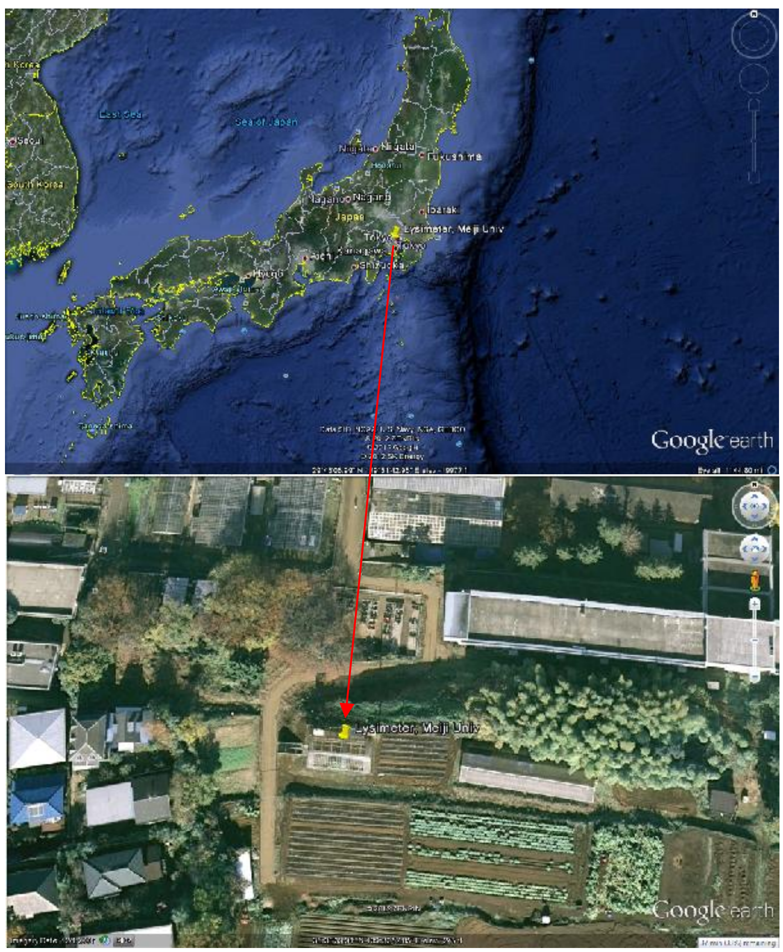


Figure 54. Experimental field in Meiji University, Japan

There were two experiments; the first was conducted with lysimeters and the second one with the pots. In the lysimeter experiment, there were six lysimeters, each lysimeter was 2 x 2 m^2 in area. In the pot experiment, six pots were used. The diameter of the pot was 25 cm and the height was 30 cm. In all experiments, we used a Japonica rice variety (Koshihikari) with SRI elements consisting of single transplanting of young seedling and spaced at 25 cm x 25 cm for lysimeters. The soil type of the lysimeter experiment was an Andosol, while the Kanto loam for the pot experiment.

For the measurements of greenhouse gases, methane and nitrous oxide were determined twice a week for the lysimeter experiment and once a week for the pot experiment using a chamber method. The closed chamber with the size of 30 cm in wide, 60 cm in long and 100 cm in high for lysimeter experiment, and 30 cm in diameter and 100 cm in high for pot experiment were used. During measurement, the chamber was placed over single paddy rice for pot experiment and six paddies rice for lysimeter experiment. After placement of the chamber (time = 0), the gas sample was taken from the chamber as well as from the ambient. Then, every 10 minutes, the gas sample was taken from the chamber within 30 minutes. The sampling gas was analyzed using a gas chromatograph to determine methane and nitrous oxide emissions.

Then, the fluxes of the gases were calculated from temporal increase/decrease of gas concentration inside of the chamber per unit time. A positive value of the flux indicates gas emission, while a negative value indicates gas uptake. The total emissions were calculated by integrating the fluxes for the period of cultivation using Simpson’s role numerical analysis described by the following equation:

$$\int_a^b f(x)dx \approx \frac{b-a}{6}\left[f(a) + 4f(\frac{a+b}{2}) + f(b) \right] \qquad (27)$$

where a and b are time points in the cultivation period (d)

Meanwhile, GWP was calculated based on the following formula:

$$\mathrm{GWP} = \mathrm{CO_2\ emission} + 23\,\mathrm{x}\,\mathrm{CH_4\ emission} + 296\,\mathrm{x}\,\mathrm{N_2O\,emission} \quad (28)$$

where GWP is global warming potential (g CO_2 – C equivalent).

7.2.1 Water management

Three irrigation regimes were applied both in the lysimeter and the pot experiments with two replications. The details in each regime for the lysimeter experiment was shown in Figure 55, while those in the pot experiment was shown in Figure 56.

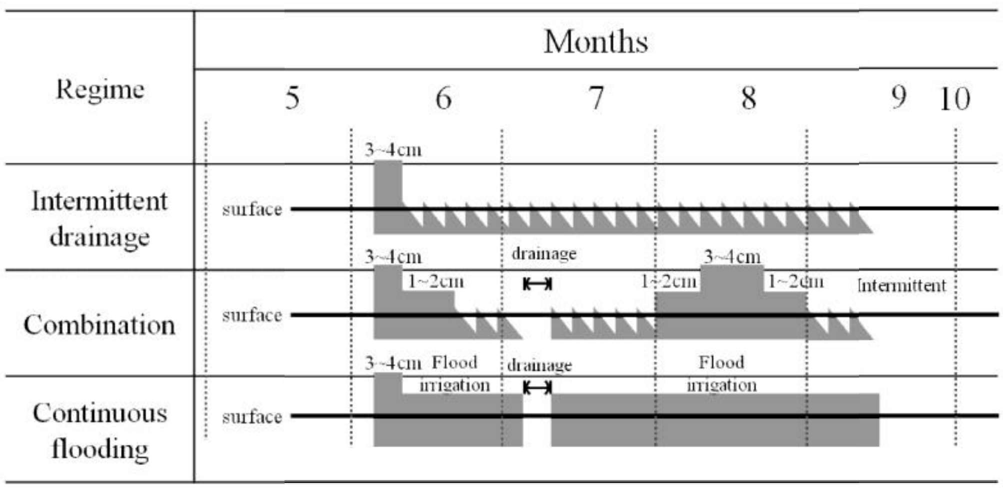


Figure 55. Irrigation regimes in the lysimeter experiment (Kudo 2012)

For all regimes in the lysimeter experiment, flooding water (3-4 cm depth) was applied in the first week of cultivation period. Then, the regime was divided into three regimes, i.e. intermittent drainage, combination and continuous flooding. For the intermittent drainage regime, the field was maintained with a water level at the soil surface and then was dried for 3 days. For the combination regime, the water level was maintained at 1-2 cm depth for two weeks, and then the mid-season drainage was applied. Hereafter, flooding water with 1-4 cm depth was applied until the end of the third stage and then the water was drained in the end of cultivation period. For the control, the continuous flooding regime was applied by maintaining the water level at 1-2 cm in which drainage was performed for several days in the second growth stage (Figure 55).

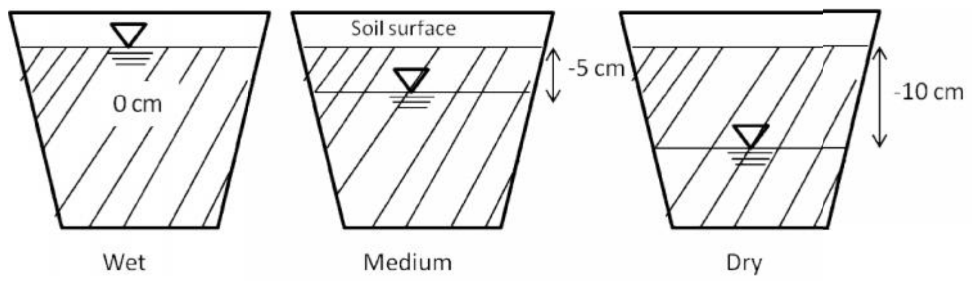


Figure 56. Irrigation regimes in the pot experiment

Meanwhile for the pot experiment, the water level was kept at the soil surface until 20 days after transplanting. Then, the regime was divided into three regimes, i.e., wet, medium, and dry regimes. The water level was kept at 0 cm, -5 cm and -10 cm from the soil surface for the wet, medium and dry regimes, respectively (Figure 56).

As the plant parameters, plant height and tillers/hill were measured twice a week, and then the averages at the harvesting time were compared between the regimes. Also, root length, weight, grain yield and biomass were investigated at the harvesting time point.

For root length and weight measurement in the lysimeter experiment, root of single paddy rice was selected randomly in each plot after harvesting. The soil with the size of 30 x 30 x 30 cm^3 was excavated carefully including the root. Then, the soil including the root was washed carefully, and the root was dried within a day. Hereafter, root length and weight were measured manually. For the pot experiment, each root of plant in each plot was taken out carefully by washing the soil to separate the soil and the root. Then, after removing the soil, the root was dried and weighted.

For grain yield and biomass measurement in the lysimeter experiment, all of plants in each plot were harvested; the grain was removed from the plants by machine and then it was weighted and converted in unit of ton/ha. Here, the weight of biomass was equal to the weight of straw and it was weighted after removing the grain. For the pot experiment, since single plant was used in each pot, the grain yield was determined by removing the grain from the plant manually and then it was weighted as well as straw yield. Here, we used unit of g/hill for grain and straw yield for the pot experiment.

Effects of irrigation regimes on plant growth, yield and greenhouse gas emissions were analyzed by analysis of variance and least significant differences (LSD) test at the $p<0.05$ significant level between regimes.

7.3 Results and Discussion

7.3.1 Effects of irrigation regime on plant growth, yield and water productivity

Table 11 shows effects of irrigation regime on the plant parameters in the lysimeter experiment. The highest plant, most tillers/hill, and number of panicles were produced by the continuous flooding regime. However, producing the highest plant, most tillers/hill and number of panicle did not correspond to the production of highest grain yield. The combination regime produced the highest grain yield because this regime produced the greatest number of spikelets per panicle. These results indicated that under the combination regime with the application of mid-season drainage, an aerobic soil condition was developed. This condition is effective to develop more spikelets and to avoid spikelet sterility particularly around flowering time (Bouman et al. 2005).

The intermittent drainage regime produced the lowest grain yield because the numbers of panicles and spikelets were lowest among the regimes. However, the highest root length and the heaviest root weight were obtained under the intermittent drainage regime. These results revealed that the plant enhanced root length to find the water in soil under the driest condition, and as the result, root weight increased.

Table 11. Effects of irrigation regime on plant parameters in the lysimeter experiment (Kudo 2012)

Plant Parameters	Irrigation regimes Continuous flooding	 Combination	 Intermittent drainage
Plant Height (cm)	100.63 ± 0.94a	96.73 ± 1.04b	95.25 ± 2.38b
Tillers/hill	18 ± 0.94a	15 ± 0.94b	10 ± 0.24c
Numbers of panicle (m^{-2})	224 ± 45.25a	214.4 ± 27.15a	161.6 ± 29.42a
Numbers spikelet per panicle	101 ± 5.40a	111 ± 2.91b	87 ± 0.7c
Root length (cm)	27.5 ± 0.71a	22.5 ± 4.95a	34.5 ± 0.71b
Root weight (g/hill)	145.27 ± 3.54a	154.52 ± 7.80a	188.33 ± 37.75a
Biomass (t/ha)	10.58 ± 0.32a	11.43 ± 0.32b	6.63 ± 0.18c
Grain yield (t/ha)	4.32 ± 1.05a	4.69 ± 0.79a	2.64 ± 0.58b

the values showed the average ± standard deviation
a, b, c significant at $p<0.05$

Table 12. Effects of irrigation regime on plant parameters in the pot experiment

Plant Parameters	Irrigation regimes Wet	 Medium	 Dry
Plant Height (cm)	82.5 ± 2.83a	85 ± 2.83a	81.05 ± 0.64a
Tillers/hill	41 ± 5.66a	27 ± 3.54b	29 ± 4.24b
Root weight (g/hill)	165.58	189.50	214.98
Straw yield (g/hill)	150 ± 0a	100 ± 14.14b	100 ± 14.14b
Grain yield (g/hill)	92.54 ± 3.98a	57.86 ± 12.45b	58.95 ± 8.53b

the values showed the average ± standard deviation
a, b, c significant at $p<0.05$

In the pot experiment, the highest grain yield and straw yield were obtained under the wet regime because the greatest tillers/hill was also obtained under this regime (Table 12). However, producing more grain and straw yields were not correlated to the root development. The heaviest root weight was obtained under the dry regime. This result showed the similar situation as the lysimeter experiment. When the soil condition is drier, the plant tries to find water in the soil by enhancing the root, thus root weight increased.

Table 13. Effects of irrigation regime on water productivity in the lysimeter experiment

Parameters	Irrigation regimes		
	Continuous flooding	Combination	Intermittent drainage
Irrigation (mm)	1537	1277	1203
Precipitation (mm)	147	147	147
Water productivity (g grain/kg water)	0.26	0.33	0.20
Water saving (%)	-	16.92%	21.76%

Table 13 shows effects of irrigation regime on water productivity in the lysimeter experiment. Overall, the water productivity was lower than the field experiment conducted in Indonesia (chapter 6). This may be attributed to more water input in irrigated of the plots but lower yields were obtained. In this experiment, the combination regime has the highest water productivity because the highest yield was obtained with less water input in the irrigation. By this regime, the water can be saved up to 16.92%.

Table 14. Effects of irrigation regime on water productivity in the pot experiment

Parameters	Irrigation regimes		
	Wet	Medium	Dry
Irrigation (mm)	688	432	314
Precipitation (mm)	65	65	65
Total water input (equal to kg water)	37.65	24.85	18.95
Water productivity (g grain/kg water)	2.46	2.33	3.11
Water saving (%)	-	37.21%	54.36%

In the pot experiment, water productivity was the highest among the experiments. The highest water productivity was obtained under the pot experiment because the highest grain yield was obtained with the minimum water input (Table 12 and Table 14).

Among the pot experiment regimes, the dry regime had the highest water productivity but the lower grain yield than that of the wet regime. This result was contrary to the lysimeter experiment in which the highest yield was produced under the regime, thus the highest water productivity was obtained. The dry regime achieved the highest water productivity because the minimum water input was accompanied in the irrigation of the pot. In this regime, the total water input was 54.36% lower than that of the wet regime (Table 14).

7.3.2 Effects of irrigation regime on global warming potential

Table 15 shows effects of irrigation regime on GWP in the lysimeter experiment. It was clearly observed that methane had a negative correlation to nitrous oxide as reported in a previous research (Cai et al. 1997). The intermittent drainage regime released the lowest methane emission because the field was the driest among the regimes. This was probably due to the availability of oxygen and sulfate in the soil, thus methanogens, methane producers, should have limited activity of organic matter decomposition (Bouwman 1990; Cicerone and Oremland 1988). However, this condition promoted the soil to release nitrous oxide to the air. Therefore, this regime most significantly contributed to nitrous oxide emission among the regimes. On the other hand, the continuous flooding regime released the highest amount of methane from the soil. Anaerobic condition was developed in this regime, thus oxygen and sulfate were scarce. This condition promoted methane producer activity during organic matter decomposition, so the methane emission increased.

Table 15. Effects of irrigation regime on GWP in the lysimeter experiment (Kudo 2012)

	Irrigation regimes		
Parameters	Continuous flooding	Combination	Intermittent drainage
CH_4 (kg/ha/season)	12.47 ± 1.49a	3.97 ± 1.26b	-0.84 ± 1.54c
N_2O (kg/ha/season)	0.68 ± 0.26a	0.59 ± 0.07a	1.28 ± 0.25b
GWP (kg/ha/season)	489.37 ± 43.47a	265.21 ± 48.68b	358.67 ± 39.25b

the values showed the average ± standard deviation
a, b, c significant at $p<0.05$

The combination regime contributed to the lowest GWP by releasing methane and nitrous oxide at a medium level (Table 15). Therefore, this regime was the best strategy for mitigating GWP. By this regime, GWP can be reduced significantly, up to 46%. In addition, this regime was also the best regime to produce a higher yield than the others with the minimum water input as explained previously.

Table 16. Effects of irrigation regime on GWP in the pot experiment

Parameters	Irrigation regimes		
	Wet	Medium	Dry
CH_4 (kg/ha/season)	18.32	4.68	-0.56
N_2O (kg/ha/season)	3.61	6.86	5.00
GWP (kg/ha/season)	1488.98	2138.50	1467.29

A negative correlation between methane and nitrous oxide emissions was also found in the pot experiment (Table 16). The dry regime released the lowest amount of methane, while the wet regime caused the highest methane emission. The medium regime was supposed to be the best regime as the mitigation strategy. However, the result showed that this regime most significantly contributed to GWP among the regimes. For the mitigation strategy in the pot experiment, the dry regime was the best among the regimes with the highest water productivity. However, this regime produced a grain yield lower than the wet regime.

7.4 Conclusions

In this chapter, effects of irrigation regime on greenhouse gas emissions were examined in the lysimeter and the pot experiments. In the lysimeter experiment, the combination regime was the best mitigation strategy among the regimes producing the highest yield and obtaining the highest water productivity. In this regime, GWP for SRI paddy field can be reduced up to 46% with the application of mid-season drainage during cultivation period. Meanwhile, the dry regime contributed to the lowest GWP with the highest water productivity in the pot experiment. However, this regime produced a grain yield of lower than that for the wet regime.

Chapter 8: General Discussion

Water management is a crucial factor in SRI application in the real field. By adopting AWDI regime, water input can be reduced significantly. However, this regime is vulnerable to water shortage in the field that decreases the yield significantly. As a result, few farmers in Indonesia are interested in applying SRI in their fields. In addition, inappropriate water management contributes to negative impact on the environment by releasing large amounts of greenhouse gases from the paddy field. This situation occurs when there is no reference of optimal SRI water management during cultivation period.

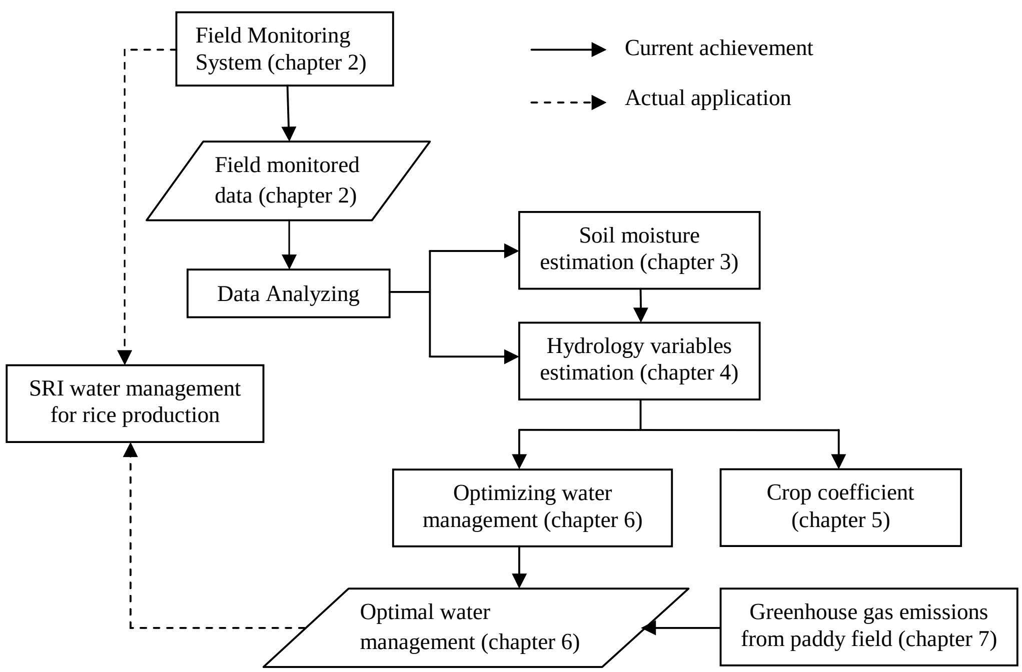


Figure 57. Intercorrelation among the chapters in this study

We proposed a novel method to optimize water management of SRI paddy fields according to three cropping season experiments by combining field monitored data and some analyses methods in maximizing yield and water productivity simultaneously. Field monitoring is important to prevent water shortage in the field by applying AWDI regime under SRI. Some processes, from data collection to data analyses, were carried out to achieve the purposes as presented in Figure 57. The daily field data were needed to identify the relationship between plant and environment before performing optimization process.

Field monitoring was performed to collect precise field data for facilitating the user in observing field data without coming to the field daily. We initiated to apply a new technology of field monitoring for SRI paddy field in Indonesia by adopting quasi real-time monitoring. During the three cropping seasons, the new FMS well monitored the SRI paddy field daily providing field images, numeric, and graphic data (chapter 2). Although this monitoring did not send real-time data, the data were stored in the field data loggers and sent daily to the server. The daily field image was useful to observe plant growth, while the daily field numeric data, i.e., meteorological and soil moisture data, were required as basic information to optimize SRI water management. In addition, when soil moisture data were lost due to unexpected problems in the field, meteorological data were useful to estimate soil moisture using the NN model (chapter 3).

The meteorological and soil moisture data, both measured and estimated in chapter 2 and 3, were then used to estimate non-measurable hydrology variables, i.e., irrigation water, ETc, runoff, and percolation, by performing water balance analysis using Excel Solver (chapter 4). The hydrology data were important to observe plant response to available water in the field which is represented by crop coefficient (chapter 5) and to optimize water management by determining soil moisture combination to maximize both yield and water productivity simultaneously (chapter 6).

The linear program with Excel Solver method was reliable in estimating the hydrology variables (chapter 4) as well as crop coefficient (chapter 5) indicated by well matching trends of observed and calculated values of soil moisture. The Excel Solver method can be used to find the solution not only for linear equations with constraint parameters as adopted in this study but also non-linear equations with constraint or unconstraint parameters (Arora 2012). Commonly, Excel Solver is used to find coefficients in linear or non-linear equations (Walsh and Diamond

1995). To our knowledge, this is the first study on estimation of the variables by using Excel Solver.

Eventually, all parameters both measured and estimated data to optimize SRI paddy water management were completely available (chapters 2, 3 and 4), we proposed GA model to optimize SRI water management by finding a soil moisture combination for maximizing yield and water productivity (chapter 6). According to the empirical data and identification results, the GA model recommended a soil moisture combination of wet, wet, medium, and dry levels for initial, crop development, mid-season, and late season growth stages, respectively. We called the optimal irrigation regime as W-W-M-D regime because it is easily recognized by the people.

The optimal soil moisture value was 0.622 and 0.563 cm^3/cm^3 for the initial and crop development stages, respectively. The values were maximum value for the initial stage and the minimum value for the crop development stage in third cropping season. The optimal soil moisture is a maximum value in the initial stage because the plants need more water for initial growth especially vegetative phase in developing root, stem, leaf and tiller. The maximum value of soil moisture is over the saturation condition indicating shallow standing water is required in the field to prevent the weeds growing rapidly. However, deep standing water should be avoided because rice plants cannot grow well with limited oxygen concentration under flooding conditions (Uphoff et al. 2011). Then, soil moisture condition could be decreased into minimum value of wet level in the crop development stage to increase water use efficiency when roots have well developed in the previous stage. This argument was supported by the empirical data in chapter 6 that yield increased significantly when soil moisture was over saturation border in the initial stage, and then it declined close to saturation border in the crop development stage.

In the mid-season stage, the optimal soil moisture was 0.522 cm^3/cm^3 (medium level). Soil moisture at medium level is required in the mid-season stage when plants are focusing on their generative phase (flowering and panicle development). The medium level, i.e., the irrigation threshold at the field capacity (pF 2.54), is important in developing an aerobic soil condition to avoid spikelet sterility particularly around flowering time (Bouman et al. 2005). Based on empirical data in chapter 6, yield increased when soil moisture was close to field capacity border. Increasing yield was obtained probably due to proper situation occurred in the field when oxygen was available optimally, thus allowed plants to produce more spikelet.

The medium level in the mid-season stage was also supposed to be an affective option to reduce greenhouse gas emissions from paddy field. This argument was supported by the result of lysimeter experiment (chapter 7) in which combination regime with the application of mid-season drainage produced the highest yield and water productivity and contributed lowest GWP among the regimes. The lowest contribution to GWP was caused by reducing methane emission significantly when the water was drained in the mid-season stage. This result agreed with the previous studies that mid-season drainage irrigation was an effective option to reduce the net GWP from paddy fields (Towprayoon et al. 2005; Akiyama et al. 2005).

Finally, in the late season stage, soil moisture of 0.350 cm^3/cm^3 at dry level could be applied in the field to save more water because all plant organs are perfectly developed. In this stage, minimum water input could be supplied in the field because minimum plant water requirement is needed as represented by lowest crop coefficient (chapter 5). Commonly, crop coefficient declines rapidly to its minimum value in the late season stage for most crops indicated that minimum water is required as reported in previous studies (Uphoff et al. 2011; Doorenbos and Kassam 1979; Zawawi et al. 2010)).

The W-W-M-D regime is the main finding in this study. All of the arguments above from empirical data and previous studies show the reliability of this finding in maximizing yield and water productivity and releasing the lowest amounts of greenhouse gases from SRI paddy field. By this regime, yield and water productivity were estimated to rise up to 6.33% and 25.09%, respectively.

The finding is simple and easily adopted by the farmers who are interested in applying SRI in their fields. For actual application, this finding can be used as a reference to determine irrigation planning in SRI paddy field for rice production (Figure 57). We expect, by considering this finding, yield and water productivity of rice production could be raised with the minimum negative environmental impact.

For improving the model in the future, greenhouse gas emissions data should be inputted in the objective function of the model as the strategy to minimize negative environmental impact simultaneously. Consequently, field monitoring should be equipped with greenhouse gas sensors to monitor the emissions together with meteorological and soil parameters.

In addition, the proposed method could be applied also to optimize water management not only for SRI paddy fields but also other agricultural fields if they are monitored by the FMS. Before applying the method, we should consider real field conditions including the characteristics of soil, crop and climate. Therefore, some modifications and adjustments of the model are probably needed for the application in every location.

Chapter 9: Conclusions

9.1 Conclusions

In this study, we developed the field monitoring system (FMS) for SRI paddy field in Indonesia. The monitoring technology adopted the concept of quasi real-time monitoring with more power saving and Internet cost effectiveness than the real time monitoring. According to the FMS data, we proposed an integrated data analysis using some models to optimize water management to maximize yield and water productivity. The evaluation and optimization results can be concluded as the following points:

1. FMS was effective, efficient and reliable in monitoring SRI paddy field in Indonesia in long-term experiments
2. We proposed an integrated data analysis combining monitoring data to optimize water management in maximizing yield and water productivity.
3. The proposed methods consisted of the neural network (NN) model for soil moisture and plant growth estimation, the linear program with Excel Solver method for non-measurable water balance variables and crop coefficient (Kc) value estimation, multiple linear regression analysis for yield estimation, and a genetic algorithm (GA) model for water management optimization.
4. The results showed that the proposed methods were reliable as indicated by their acceptable performances.
5. According to the empirical data, yield and water productivity were clearly affected by irrigation regime.
6. Following one cropping season in Japan, greenhouse gas emissions were clearly affected by the irrigation regimes adopted in the lysimeter and the pot experiments.
7. As the greenhouse gas mitigation strategy, the combination regime was found to be the best to produce more rice yields with saved water consumption up to 16.92% and a significant reduction of GWP of 46% in the lysimeter experiment.

8. The GA model has found that the optimal water management was represented by the soil moisture combination of 0.622 (wet), 0.563 (wet), 0.522 (medium), and 0.350 cm^3/cm^3 (dry) for the initial, crop development, mid-season and late season growth stages, respectively.
9. We called the optimal SRI water management was W-W-M-D regime in maximizing yield and water productivity and supposed releasing the lowest amount of GWP

9.2 Future challenges

For the future development and application, the proposed methods can be applied not only for SRI paddy fields but also for monitoring other crops by the FMS with some adjustments. Also, according to the field experiments both in Indonesia and Japan, some challenges emerged as issues to be considered for future researches using the FMS as enlisted below:

1. Connecting the FMS to the greenhouse gas sensors and their data loggers, thus the integrated data analysis can be used not only to optimize yield and water productivity but also to minimize greenhouse gas emissions.
2. Optimizing water management for SRI paddy field can be performed by considering climate change scenarios using long-term monitored data.
3. Monitoring plant growth using image processing methods based on field image data will be feasible. Then, plant growth and yield estimations can be performed without visiting the fields.
4. Exploring effects of other SRI elements such as age of the seedling and fertilizer on the yield will be meaningful for improvement of SRI application.

References

Abdel-Fattah YR, El-Enshasy HA, Soliman NA, El-Gendi H (2009) Bioprocess Development for Production of Alkaline Protease by Bacillus pseudofirmus Mn6 Through Statistical Experimental Designs. J Microbiol Biotechn 19 (4):378-386. doi:10.4014/jmb.0806.380

Akiyama H, Yagi K, Yan XY (2005) Direct N2O emissions from rice paddy fields: Summary of available data. Global Biogeochem Cy 19 (1). doi:10.1029/2004gb002378

Allen RG, Pareira LS, Raes D, Smith M (1998) Crop Evapotranspiration Guidelines for computing crop water requirements. FAO - Food and Agriculture Organization of the United Nations, Rome

Anbumozhi V, Yamaji E, Tabuchi T (1998) Rice crop growth and yield as influenced by changes in ponding water depth, water regime and fertigation level. Agr Water Manage 37 (3):241-253

Arora JS (2012) Chapter 6 - Optimum Design with Excel Solver, Introduction to Optimum Design (Third Edition). Academic Press, Boston. doi:10.1016/B978-0-12-381375-6.00006-1

Barison J, Uphoff N (2011) Rice yield and its relation to root growth and nutrient-use efficiency under SRI and conventional cultivation: an evaluation in Madagascar. Paddy Water Environ 9 (1):65-78. doi:10.1007/s10333-010-0229-z

Barker R, Dawe D, Tuong TP, Bhuiyan SI, Guerra LC (2000) The outlook for water resources in the year 2020: challenges for research on water management in rice production. International Rice Commission Newsletter 49:7-21

Basheer IA, Harmeer M (2000) Artificial Neural Networks: fundamentals, computing, design, and application. Journal of Microbiological Methods 43:3-31

Bouman BAM (2001) Water-efficient management strategies in rice production. International Rice Research Note 26.2.

Bouman BAM, Humphreys E, Tuong TP, Barker R (2007) Rice and water. Advances in Agronomy 92:187-237. doi:10.1016/S0065-2113(04)92004-4

Bouman BAM, S.Peng., Castaneda AR, Visperas RM (2005) Yield and water use of irrigated tropical aerobic rice systems. Agr Water Manage 74:87-105. doi:10.1016/j.agwat.2004.11.007

Bouman BAM, Tuong TP (2001) Field water management to save water and increase its productivity in irrigated lowland rice. Agr Water Manage 49 (1):11-30. doi:10.1016/S0378-3774(00)00128-1

Bouwman AF (1990) Introduction. In: Bouwman AF (ed) Soil and the Greenhouse Effects. John Wiley & Sons, New York, United States,

Cai ZC, Xing GX, Yan XY, Xu H, Tsuruta H, Yagi K, Minami K (1997) Methane and nitrous oxide emissions from rice paddy fields as affected by nitrogen fertilisers and water management. Plant Soil 196 (1):7-14

Chapagain T, Yamaji E (2010) The effects of irrigation method, age of seedling and spacing on crop performance, productivity and water-wise rice production in Japan. Paddy Water Environ 8 (1):81-90. doi:10.1007/s10333-009-0187-5

Chen RS, Pi LC, Huang YH (2003) Analysis of rainfall-runoff relation in paddy fields by diffusive tank model. Hydrol Process 17 (13):2541-2553. doi:10.1002/hyp.1266

Chen S, Billings SA, Grant PM (1990) Non-linear system identification using neural network. Int J Control 51 (6):1191-1214

Cho JY (2003) Seasonal runoff estimation of N and P in a paddy field of central Korea. Nutr Cycl Agroecosys 65 (1):43-52. doi:10.1023/A:1021819014494

Choi JD, Park WJ, Park KW, Lim KJ (2012) Feasibility of SRI methods for reduction of irrigation and NPS pollution in Korea. Paddy Water Environ published online by Springerlink Feb. 9. doi:10.1007/s10333-012-0311-9

Cicerone RJ, Delwiche CC, Typer SC, Zimmermann PR (1992) Methane emissions from California rice paddies with varied treatments. Global Biogeochem Cy 6 (3):233-248

Cicerone RJ, Oremland RS (1988) Biogeochemical aspects of atmospheric methane. Global Biogeochem Cy 2:229-238

Dasgupta PK (2008) Chromatographic peak resolution using Microsoft Excel Solver The merit of time shifting input arrays. J Chromatogr A 1213 (1):50-55. doi:10.1016/j.chroma.2008.08.108

De Silva CS, Weatherhead EK, Knox JW, Rodriguez-Diaz JA (2007) Predicting the impacts of climate change - A case study of paddy irrigation water requirements in Sri Lanka. Agr Water Manage 93 (1-2):19-29. doi:10.1016/j.agwat.2007.06.003

Dobermann A (2004) A critical assessment of the system of rice intensification (SRI). Agr Syst 79 (3):261-281. doi:10.1016/S0308-521x(03)00087-8

Doorenbos J, Kassam AH (1979) Yield response to water. FAO Irrigation and Drainage Paper 33. FAO, Rome

Gani A, Kadir TS, Jatiharti A, Wardhana IP, Las I (2002) The System of Rice Intensification in Indonesia. In: Uphoff N, Fernandes E, Yuan LP, Peng JM, Rafaralahy S, Rabenandrasana J (eds) Assessments of the System of Rice Intensification (SRI), Sanya, China, 1-4 April 2002. Cornell International Institute for Food, Agriculture and Development, Ithaca, NY, pp 58-63

Gardjito, Rudiyanto, Agustina H, Setiawan BI, Mizoguchi M, Ito T, Priess J (2008) Environmental Monitoring with Field Server via Internet. In: LIPI and STORMA Workshop, Jakarta, 20-21 February 2008.

Goldberg DE (1989) Genetic algorithms in search optimization and machine learning. Addison-Wesley, Reading, Massachusetts

Guerra LC, Bhuiyan SI, Tuong TP, Barker R (1998) Production more rice with less water from irrigated systems. SWIM Paper 5. International Water Management Institute, Colombo, Srilanka

Hadi A, Inubushi K, Yagi K (2010) Effect of water management on greenhouse gas emissions and microbial properties of paddy soils in Japan and Indonesia. Paddy Water Environ 8:319–324. doi:10.1007/s10333-010-0210-x

Hameed KA, Mosa AKJ, Jaber FA (2011) Irrigation water reduction using System of Rice Intensification compared with conventional cultivation methods in Iraq. Paddy Water Environ 9 (1):121-127. doi:10.1007/s10333-010-0243-1

Hargreaves GH, Allen RG (2003) History and evaluation of Hargreaves evapotranspiration equation. J Irrig Drain E-Asce 129 (1):53-63. doi:Doi 10.1061/(Asce)0733-9437(2003)129:1(53)

Hashimoto Y (1997) Applications of artificial neural networks and genetic algorithms to agricultural systems. Comput Electron Agr 18 (2-3):71-72

Heinemann AB, Stone LF, Fageria NK (2011) Transpiration rate response to water deficit during vegetative and reproductive phases of upland rice cultivars. Sci Agr 68 (1):24-30. doi:10.1590/S0103-90162011000100004

Hinnell AC, Lazarovitch N, Furman A, Poulton M, Warrick AW (2009) Neuro-Drip: estimation of subsurface wetting patterns for drip irrigation using neural networks. Irrigation Sci 28 (6):535-544

Honda K, Shrestha A, Chinnachodteeranun R, Mizoguchi M, Shimamura H, Kameoka T (2008) Spinach Field Monitoring for Bridging Thai Producer and Japanese Consumer under Sensor Asia. In: SICE Annual Conference, The University Electro-Communications, Japan.

Hupet F, Vanclooster M (2001) Effect of the sampling frequency of meteorological variables on the estimation of the reference evapotranspiration. J Hydrol 243 (3-4):192-204. doi:Doi 10.1016/S0022-1694(00)00413-3

Husin YA, Murdiyarso D, Khalil MAK, Rasmussen RA, Shearer MJ, Sabiham S, Sunar A, Adijuwana H (1995) Methane Flux from Indonesian Wetland Rice - the Effects of Water Management and Rice Variety. Chemosphere 31 (4):3153-3180. doi:Doi 10.1016/0045-6535(95)00173-6

Irsyad F (2011) Analysis of Cidanau River Discharge using SWAT Application. Master Thesis. Bogor Agricultural University, Bogor

Jalota SK, Sood A, Chahal GBS, Choudhury BU (2006) Crop water productivity of cotton (Gossypium hirsutum L.)-wheat (Triticum aestivum L.) system as influenced by deficit irrigation, soil texture and precipitation. Agr Water Manage 84 (1-2):137-146. doi:DOI 10.1016/j.agwat.2006.02.003

Jensen ME, Burman RD, Allen RG (1990) Evapotranspiration and Irrigation Water Requirements. The American Society of Civil Engineers, New York,

Jury W, Horton R (2004) Soil Physics. 6th edn. John Wiley & Sons. Inc., Hoboken, New Jersey

Kalita PK, Kanwar RS, Rahman MA (1992) Modeling Percolation Losses from a Ponded Field under Variable Water-Table Conditions. Water Resour Bull 28 (6):1023-1036. doi:10.1111/j.1752-1688.1992.tb04014.x

Kalman RE (1960) A new approach to linear filtering and prediction problems. Transactions of the ASME–Journal of Basic Engineering 82 (Series D):35-45

Kim HK, Jang TI, Im SJ, Park. SW (2009) Estimation of irrigation return flow from paddy fields considering the soil moisture. Agr Water Manage 96:875–882. doi:10.1016/j.agwat.2008.11.009

Ko J, Piccinni G (2009) Corn yield responses under crop evapotranspiration-based irrigation management. Agr Water Manage 96 (5):799-808. doi:DOI 10.1016/j.agwat.2008.10.010

Kobayashi K, Salam MU (2000) Comparing Simulated and Measured Values Using Mean Squared Deviation and its Components. Agron J 92:345-352

Kudo Y (2012) Personal Communication.

Kukal SS, Aggarwal GC (2002) Percolation losses of water in relation to puddling intensity and depth in a sandy loam rice (Oryza sativa) field. Agr Water Manage 57 (1):49-59

Kumar KVK, Yellareddygari SK, Reddy MS, Kloepper JW, Lawrence KS, Zhou XG, Sudini H, Groth DE, Raju SK, MillerMILLER7 ME (2012) Efficacy of Bacillus subtilis MBI 600 Against Sheath Blight Caused by Rhizoctonia solani and on Growth and Yield of Rice. Rice Science 19 (1):55-63. doi:10.1016/S1672-6308(12)60021-3,

Kuo SF, Merkley GP, Liu CW (2000) Decision support for irrigation project planning using a genetic algorithm. Agr Water Manage 45 (3):243-266

Li XL, Yuan WP, Xu H, Cai ZC, Yagi K (2011) Effect of timing and duration of midseason aeration on CH4 and N2O emissions from irrigated lowland rice paddies in China. Nutr Cycl Agroecosys 91 (3):293-305. doi:DOI 10.1007/s10705-011-9462-0

Li YH, Cui YL (1996) Real-time forecasting of irrigation water requirements of paddy fields. Agr Water Manage 31 (3):185-193

Lin XQ, Zhu DF, Lin XJ (2011) Effects of water management and organic fertilization with SRI crop practices on hybrid rice performance and rhizosphere dynamics. Paddy Water Environ 9 (1):33-39. doi:10.1007/s10333-010-0238-y

Luo YF, Khan S, Cui YL, Peng SZ (2009) Application of system dynamics approach for time varying water balance in aerobic paddy fields. Paddy Water Environ 7 (1):1-9. doi:10.1007/s10333-008-0146-6

Maleki N, Haghighi B, Safavi A (1999) Evaluation of formation constants, molar absorptivities of metal complexes, and protonation constants of acids by nonlinear curve fitting using microsoft excel solver and user-defined function. Microchem J 62 (2):229-236

Manzano VJP, Mizoguchi M, Mitsuishi S, Ito T (2011) IT field monitoring in a Japanese system of rice intensification (J-SRI). Paddy Water Environ 9 (2):249-255. doi:10.1007/s10333-010-0226-2

Mizoguchi M, Ito T, Arif C, Mitsuishi S, Akazawa M (2011) Quasi real-time field network system for monitoring remote agricultural fields. In: SICE Annual Conference 2011, Waseda University, Tokyo, Japan, 13-18 September 2011. pp 1586-1589

Mizoguchi M, Ito T, Mitsuishi S (2009) Ubiquitous Monitoring of Agricultural Fields in Asia for Safe Agricultural Production Management. In: PAWEES 2009 Conference on Promising Practices for the Development of Sustainable Paddy Fields Bogor, Indonesia, 2009. pp GI.15 : 11-18

Mizoguchi M, Mitsuishi S, Ito T, Oki K, Ninomiya S, Hirafuji M, Fukatsu T, Kiura T, Tanaka K, Toritani H, Hamada H, Honda K (2008) Real-time monitoring of soil information in agricultural fields in Asia using Field server. In: 1st Global workshop on High Resolution Digital Soil Sensing and Mapping, Sydney, Australia, 2008. pp 19-24

Mohan S, Arumugam N (1994) Irrigation crop coefficient for lowland rice. Irrigation and Drainage Systems 8:159-176. doi:10.1007/BF00881016

Morimoto T, Hashimoto Y (2000) AI approaches to identification and control of total plant production systems. Control Engineering Practice 8:555-567

Morimoto T, Ouchi Y, Shimizu M, Baloch MS (2007) Dynamic optimization of watering Satsuma mandarin using neural networks and genetic algorithms. Agr Water Manage 93:1-10. doi:10.1016/j.agwat.2007.06.013

Morrison FA (2005) Using the Solver add-in in Microsoft Excel®. Michigan Technological University Web. http://www.chem.mtu.edu/~fmorriso/cm4650/Using_Solver_in_Excel.doc.

Mosier AR, Duxbury JM, Freney JR, Heinemeyer O, Minami K (1996) Nitrous oxide emissions from agricultural fields: Assessment, measurement and mitigation. Plant Soil 181 (1):95-108

NARO (2007) Database-Model cooperation system project. http://www.agmodel.net/DataModel/. Accessed 10 October 2011

NARO (2009) IT-AG national project. http://model.job.affrc.go.jp/FieldServer/default.htm. Accessed 10 October 2011

Nemoto K, Morita S, Baba T (1995) Shoot and Root Development in Rice Related to the Phyllochron. Crop Sci 35 (1):24-29

Neue HU, Heidmann PB, Scharpenseel HW (1990) Organic matter dynamics, soil properties, and cultural practices in rice lands and their relationship to methane production. In: Bouwman AF (ed) Soil and the Greenhouse Effect. John Wiley & Sons, New York, United States, pp 457-466

Nugroho AS (2003) Information analysis using soft computing - the applications to character recognition, meterological prediction and bioinformatics problem. PhD Disertation, Nagoya Institute of Technology, Nagoya, Japan

Nugroho SG, Lumbanraja J, Suprapto H, Sunyoto, Ardjasa WS, Haraguchi H, Kimura M (1994) Effect of Intermittent Irrigation on Methane Emission from an Indonesian Paddy Field. Soil Sci Plant Nutr 40 (4):609-615

Persaud N, Zhou X, Lesolle D (2007) Preliminary test of the Penman-Monteith equation for estimating daily reference evapotranspiration in Botswana. Int J Agric Res 2:53-61. doi:10.3923/ijar.2007.53.61

Raju KS, Kumar DN (2004) Irrigation planning using Genetic Algorithms. Water Resour Manag 18 (2):163-176

Raju SK, Kumar DN, Duck L (2006) Artificial neural networks and multicriterion analysis for sustainable irrigation planning. Computers and Operations Research 33:1138-1153

Ramanathan V, Cicerone RJ, Singh HB, Kiehl JT (1985) Trace Gas Trends and Their Potential Role in Climate Change. J Geophys Res-Atmos 90 (Nd3):5547-5566

Reshmidevi TV, Jana R, Eldho TI (2008) Geospatial estimation of soil moisture in rain-fed paddy fields using SCS-CN-based model. Agr Water Manage 95 (4):447-457. doi:10.1016/j.agwat.2007.11.002

Sakthivadivel R, M. , Renshaw JB, Silver, Birley MH, Konradsen F (2001) Alternate wet/dry Irrigation In Rice Cultivation: a Pratical Way to Save Water and Control Malaria and Japanese Encephalitis? International Water Management Institute, Colombo, Sri Lanka

San-oh Y, Mano Y, Ookawa T, Hirasawa T (2004) Comparison of dry matter production and associated characteristics between direct-sown and transplanted rice plants in a submerged paddy field and relationships to planting patterns. Field Crop Res 87:43-58

Sato S, Uphoff N (2007) A review of on-farm evaluation of system of rice intensification (SRI) methods in eastern Indonesia. Article in CAB

Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources

Sato S, Yamaji E, Kuroda T (2011) Strategies and engineering adaptions to disseminate SRI methods in large-scale irrigation systems in Eastern Indonesia. Paddy Water Environ 9 (1):79-88. doi:10.1007/s10333-010-0242-2

Setiawan BI, Mizoguchi M, Arif C, Ito T (2010) Environmental Monitoring System on the Advancement of the System of Rice Intensification in Asian Countries. In: AFITA 2010 International Conference: the Quality Information for Competitive Agricultural based Production System and Commerce, Bogor, Indonesia, 3-7 October 2010.

Setyanto P, Makarim AK, Fagi AM, Wassman R, Buendia LV (2000) Crop management affecting methane emissions from irrigated and rainfed rice in Central Java (Indonesia). Nutr Cycl Agroecosys 58:85-93

Sheehy JE, Peng S, Dobermann A, Mitchell PL, Ferrer A, Yang JC, Zou YB, Zhong XH, Huang JL (2004) Fantastic yields in the system of rice intensification: fact or fallacy? Field Crop Res 88 (1):1-8. doi:10.1016/j.fcr.2003.12.006

Shih SF (1987) Using crop yield and evapotranspiration relations for regional water requirement estimation Water Resour Bull 23 (3):435-442. doi:10.1111/j.1752-1688.1987.tb00821.x

Shih SF, Rahi GS, Snyder GH, Harrison DS, Smajstrla AG (1983) Rice Yield, Biomass, and Leaf-Area Related to Evapo-Transpiration. T Asae 26 (5):1458-1464

Sinclair TR, Cassman KG (2004) Agronomic UFOs. Field Crop Res 88 (1):9-10. doi:10.1016/j.fcr.2004.01.001

Smith CJ, Brandon M, Patrick WH (1982) Nitrous-Oxide Emission Following Urea-N Fertilization of Wetland Rice. Soil Sci Plant Nutr 28 (2):161-171

Smith SJ, Wigley ML (2000) Global warming potentials: 1. Climatic implications of emissions reductions. Climatic Change 44 (4):445-457

Snyder CS, Bruulsema TW, Jensen TL (2007) Best Management Practices to Minimize Greenhouse Gas Emissions Associated with Fertilizer Use. Better crops 19 (4):16-18

Starr JL, Paltineanu IC (2002) Methods for Measurement of Soil Water Content: Capacitance Devices. In: Dane JH, Topp GC (eds) Methods of Soil Analysis: Part 4 Physical Methods. Soil Science Society of America, Inc., pp 463-474

Stoop W, Uphoff N, Kassam A (2002) A review of agricultural research issues raised by the system of rice intensification (SRI) from Madagascar: opportunities for improving farming systems for resource-poor farmers. Agr Syst 71:249-274. doi:10.1016/S0308-521X(01)00070-1

Suhardiyanto H, Arif C, Setiawan BI (2009) Optimization of EC Values of Nutrient Solution for Tomato Fruits Quality in Hydroponics System Using Artificial Neural Network and Genetic Algorithms. ITB J Sci 41 A (1):38-49. doi:10.5614/itbj.sci.2009.41.1.3

Thomas V, Ramzi AM (2011) SRI contributions to rice production dealing with water management constraints in northeastern Afghanistan. Paddy Water Environ 9 (1):101-109. doi:10.1007/s10333-010-0228-0

Topp GC (1980) ElectromagneticD etermination of Soil Water Content: Measurements in Coaxial Transmission Lines. Water Resour Res 16 (3):574-582

Towprayoon S, Smakgahn K, Poonkaew S (2005) Mitigation of methane and nitrous oxide emissions from drained irrigated rice fields. Chemosphere 59 (11):1547-1556. doi:DOI 10.1016/j.chemosphere.2005.02.009

Traore S, Wang YM, Kerh T (2010) Artificial neural network for modeling reference evapotranspiration complex process in Sudano-Sahelian zone. Agr Water Manage 97 (5):707-714. doi:DOI 10.1016/j.agwat.2010.01.002

Tu JV (1996) Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. J Clin Epidemiol 49 (11):1225-1231. doi:Doi 10.1016/S0895-4356(96)00002-9

Tuong TP, Bhuiyan SI (1999) Increasing water-use efficiency in rice production: farm-level perspectives. Agr Water Manage 40 (1):117-122

Tyagi L, Kumari B, Singh SN (2010) Water management - A tool for methane mitigation from irrigated paddy fields. Sci Total Environ 408 (5):1085-1090. doi:DOI 10.1016/j.scitotenv.2009.09.010

Tyagi NK, Sharma DK, Luthra SK (2000) Determination of evapotranspiration and crop coefficients of rice and sunflower with lysimeter. Agr Water Manage 45 (1):41-54. doi:10.1016/S0378-3774(99)00071-2

Uphoff N, Kassam A, Harwood R (2011) SRI as a methodology for raising crop and water productivity: productive adaptations in rice agronomy and irrigation water management. Paddy Water Environ 9:3-11. doi:10.1007/s10333-010-0224-4

Van der Hoek W, Sakthivadivel R, Renshaw M, Silver JB, Birley MH, Konradsen F (2001) Alternate wet/dry irrigation in rice cultivation: a pratical way to save water and control malaria and Japanese encephalitis? Research Report 47. International Water Management Institute, Colombo, Sri Lanka

Van Genuchten MT (1980) A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. Soil Sci Soc Am J 44:892-898

Vu SH, Watanabe H, Takagi K (2005) Application of FAO-56 for evaluating evapotranspiration in simulation of pollutant runoff from paddy rice field in Japan. Agr Water Manage 76 (3):195-210. doi:10.1016/j.agwat.2005.01.012

Walsh S, Diamond D (1995) Non-linear curve fitting using Microsoft Excel Solver. Talanta 42 (4):561-572. doi:10.1016/0039-9140(95)01446-I

Wang XG, Tang Z, Tamura H, Ishii M, Sun WD (2004) An improved backpropagation algorithm to avoid the local minima problem. Neurocomputing 56:455-460

Wardlaw R, Bhaktikul K (2004) Application of genetic algorithms for irrigation water scheduling. Irrig Drain 53 (4):397-414. doi:Doi 10.1002/Ird.121

Welch G, Bishop G (2006) An introduction to the Kalman Filter.

Won JG, Choi JS, Lee SP, Son SH, Chung SO (2005) Water saving by shallow intermittent irrigation and growth of rice. Plant Prod Sci 8 (4):487-492

Yang JC, Zhang JH (2010) Crop management techniques to enhance harvest index in rice. J Exp Bot 61 (12):3177-3189. doi:10.1093/jxb/erq112

Zawawi MAM, Mustapha S, Puasa Z (2010) Determination of water requirement in a paddy field at seberang perak rice cultivation area. Journal - The institution of Engineers 71 (4):32-41

Zeng LH, Lesch SM, Grieve CM (2003) Rice growth and yield respond to changes in water depth and salinity stress. Agr Water Manage 59 (1):67-75

Zhang B, Yuan SQ, Zhang JS, Li H (2008) Study of corn optimization irrigation model by genetic algorithms. In: IFIP International Federation for Information Processing, 2008. Springer, pp 121-132. doi:10.1007/978-0-387-77251-6_14

Zhao LM, Wu LH, Wu MY, Li YS (2011) Nutrient uptake and water use efficiency as affected by modified rice cultivation methods with reduced irrigation. Paddy Water Environ 9 (1):25-32. doi:10.1007/s10333-011-0257-3

Appendices

Appendix 1. FieldRouter Manual

1. Main Components and their functions

a. Modem: Internet connection through mobile phone line using specific SIM card (GSM (GPRS/EDGE) or 3G (HSDPA))
b. Timer: set up working time for FieldRouter
c. LED Indicators: the indicators of FieldRouter whether it working or not as well as its connection. They are (according to the number in Figure 58):

1. Power connection	4. Internet connection	6. Data logger
2. Operating system	5. Server connection	7. GPS
3. Modem		

d. Camera: acquires image of the field
e. LCD: display the status of FieldRouter during working time
f. Battery: stores the power from solar panel and as power source for FieldRouter
g. Charge controller: regulates the flow of electricity from the solar panel to the battery
h. Ring indicator: as a display of charge controller and it indicates the battery level and load power from the solar panel (see Figure 59 for indicators of battery level and load power)

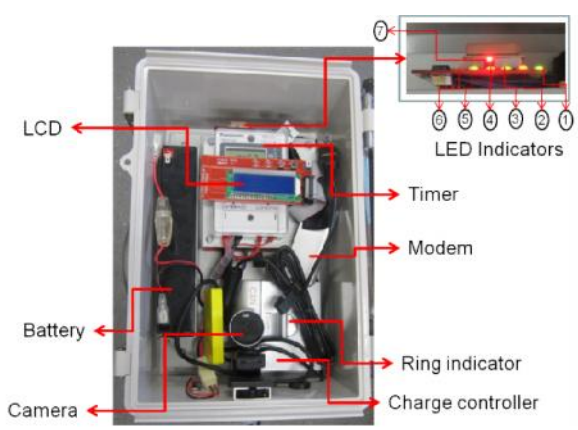


Figure 58. FieldRouter and its main components

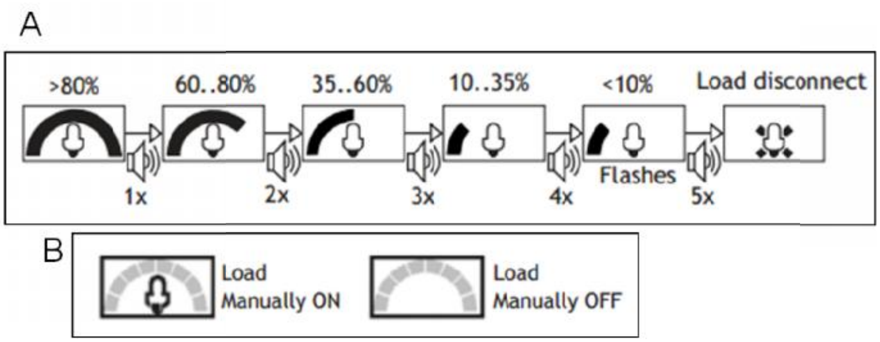


Figure 59. LCD of Ring indicators: A. Battery level; B. Load power

2. Quick Installation

1. Recognize FieldRouter number (e.g. vbox0061)
2. Insert an active SIMCARD to the modem
3. Check the battery level and make sure that is full in charge before going to the field (see Figure 59)
4. Prepare the place for FieldRouter in the field by digging the soil and make the hole with a depth of 0.5-1.5 m
5. Put the iron pipe (±50 mm in diameter, ±2 m long) to that hole and fix it
6. Put FieldRouter into that iron pipe by its screws and fix it
7. Put the solar panel on the above FieldRouter and facing south, and then fix it by its screws.
8. Confirm the battery cable and then connect the solar panel cable to FieldRouter
9. Pushing the button of Ring indicator to load power manually ON and the solar panel works well if display is running (Figure 59).
10. Test FieldRouter by the following steps:
    a. Switch ON FieldRouter manually by turning the timer into "**ON/入**" position
    b. Wait several minutes (approximately 3 minutes) for booting process
    c. While FieldRouter is working, see the indicator in the LCD to make sure that it works well. The display of LCD are:
        - Booting…
        - System up

- Detecting modem 1/5
- Detecting modem > Found:……(name of modem) > Dial: …… (SIMCARD name, e.g. b-mobile)
- Detecting modem > Connected
- Detecting modem > 1/5 Camera….
- Trying…..>/dev/ttyS3
- Upload… >Done
- Start Download
- Main menu >

d. After the display of “Main menu” coming, the process is done

e. In "Main menu" pressing black and red switch, you can browse FieldRouter function. "vbox name", "GPS", "Battery", "ping", "camera" and so on.

f. See LED Indicators. If all lights are ON that means FieldRouter working well. On the other hand, for example, if light number 4 is off that means there is problem related to the Internet connection.

g. To access the data as well as the image, open the official website. For example, if FieldRouter number is vbox0061, please open the following website:
   - http://x-ability.jp/FieldRouter/vbox0061/

h. Swicth OFF FieldRouter manually by turning the timer into “**OFF/切**” position

i. Then switch into AUTO position by turning the timer into “**AUTO/自動**” position

j. By this position, FieldRouter will be work automatically during 12.00 – 12.30 pm local time

k. Note: beep sound during testing or working time of FieldRouter. There are two kinds of beep sounds:
   - Big beep - beep from Charge Controller, consisting of 1 big beep for battery level down to 60-80%, 2 big beep for battery level down to 35-60%, 3 big beep for battery level down to 10-35%, etc.

- Small beep - beep from FieldRouter, consisting of two short beep 10 times for Modem not connected and three short beep 10 times for SIM does not work

3. Connecting FieldRouter to the data loggers

- FieldRouter can be connected to several data loggers such as from Decagon Device, Inc, USA (e.g. Em50 and Em5b data loggers) and Davis Instruments Corp, USA (e.g. Vantage Pro2 console)
- FieldRouter connected to Em50/Em5b via cable, while it connected to Vantage Pro2 console by Bluetooth connection
- Plug in the cable of FieldRouter for Decagon data loggers into “COMM PORT” for Em50 and Port number 1 for Em5b data loggers, respectively.
- Davis Field Adapter is needed to connect FieldRouter to Vantage Pro2 console
- For connecting that console to FieldRouter, “SERIAL BAUD RATE” setting should be set into “9600”.
- When FieldRouter is switched ON manually or when it is working automatically, see Light Indicator number 6, if the light is on, that mean FieldRouter is connected to the data logger

The FMS manual also can be referred by the following website:

http://info.ga.a.u-tokyo.ac.jp/fns/Main_Page

Appendix 2. Documentation during the FMS installation in the SRI paddy field

Equipment preparation

Field installation

Installed Weather Station

Installed FieldRouter

SRI paddy plots are monitored by FieldRouter

Appendix 3. Documentation during SRI cultivation in NOSC, Indonesia

Land preparing

Composting

Seedling

Transplanting

Water management

Irrigation water (1)

Irrigation water (2)

Runoff/Drainage water (1)

Runoff/Drainage water (2)

Plant growing

Harvesting

Appendix 4. Source code of NN model in visual basic language

```
'Author: Chusnul Arif
'Date: 12 December 2012
'Organization: Dept. of Global Agricultural Sciences, the University of Tokyo and Dept. of Civil and
Environmental Engineering, Bogor Agricultural University
'Corresponding author: chusnul_arif[at]ipb.ac.id or chusnul_ar[at]yahoo.com
'Website: http://chusnul_arif.staff.ipb.ac.id/

Public ni, no, nh, ncase
Public Eta, Alpha, Temp, iterasi, nl
Public itend, ite, erss, Err2
Public xinp(100, 1000) As Single
Public des(100, 1000) As Single
Public nn(5) As Integer
Public maxi(1000) As Single
Public maxo(1000) As Single
Public mixi(1000) As Single
Public mixo(1000) As Single
Public w(5, 1000, 1000) As Double
Public dw(5, 500, 500) As Double
Public dwe(5, 500, 500) As Double
Public dw2(5, 500, 500) As Double
Public dwes(5, 500, 500) As Double
Public dw2s(5, 500, 500) As Double
Public u(5, 1000) As Single
Public X(5, 1000) As Single
Public d(5, 1000) As Double
Public er(100, 1000) As Double
Public ersum(1000) As Double
Public cal(100, 1000) As Single
Public erx As Single
Public hsl(1000, 1000) As Single
Sub ReadData()
Eta = Sheet1.Cells(2, 2)
Alpha = Sheet1.Cells(3, 2)
Temp = Sheet1.Cells(4, 2)
iterasi = Sheet1.Cells(5, 2)
nl = Sheet1.Cells(6, 2)
ni = Sheet1.Cells(7, 2)
nh = Sheet1.Cells(8, 2)
no = Sheet1.Cells(9, 2)

For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i
Rem Initial weights
 'Identifikasi nilai Weight
   TW = 1
   For ii = 1 To nl
     For kk = 1 To nn(ii)
       For jj = 1 To nn(ii - 1)
          w(ii - 1, jj, kk) = 2 * Rnd - 1
          Sheet1.Cells(2 + TW, 8) = TW
          Sheet1.Cells(2 + TW, 9) = w(ii - 1, jj, kk)
          TW = TW + 1
       Next jj
     Next kk
   Next ii
End Sub

Sub ReadDataTraining()
```

```
Eta = Sheet1.Cells(2, 2)
Alpha = Sheet1.Cells(3, 2)
Temp = Sheet1.Cells(4, 2)
iterasi = Sheet1.Cells(5, 2)
nl = Sheet1.Cells(6, 2)
ni = Sheet1.Cells(7, 2)
nh = Sheet1.Cells(8, 2)
no = Sheet1.Cells(9, 2)

For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i

ncase = Sheet2.Cells(2, 2)
If ncase = "" Or "0" Then Msg = "Please fill Total Data": Response = MsgBox(Msg, Style, Title, Help,
Ctxt)
For ii = 1 To ncase
 'Identifikasi Parameter Output (no kolom pertama)
    For jj = 1 To no 'nn(nl)
     des(jj, ii) = Sheet2.Cells(ii + 6, jj + 1)
     'Sheet1.Cells(ii + 7, jj + 1) = des(jj, ii)
    Next jj
 'Identifikasi Parameter Input (ni kolom selanjutnya)
    For jj = 1 To ni 'nn(1)
     xinp(jj, ii) = Sheet2.Cells(ii + 6, jj + 1 + no)
     'Sheet1.Cells(ii + 7, jj + 1 + no) = xinp(jj, ii)
    Next jj
Next ii
End Sub

Rem Data Identification
Sub DataIdentification()
For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i

For ii = 1 To nn(1)
 mixi(ii) = Sheet2.Cells(ii + 7, 10)
 maxi(ii) = Sheet2.Cells(ii + 7, 9)
Next ii

For ii = 1 To nn(3)
 mixo(ii) = Sheet2.Cells(ii + 12, 10)
 maxo(ii) = Sheet2.Cells(ii + 12, 9)
Next ii
End Sub

Sub Desimalisasi()
'Set Nilai xinp(ii,jj) Baru (parameter Input)(Desimalisasi input : 0-1)
For ii = 1 To nn(1)
 For jj = 1 To ncase
    xinp(ii, jj) = (xinp(ii, jj) - mixi(ii)) / (maxi(ii) - mixi(ii))
 Next jj
Next ii

'Set Nilai des(ii,jj) Baru (parameter Output) (Desimalisasi output: 0.2-0.8)
For ii = 1 To nn(nl)
 For jj = 1 To ncase
   des(ii, jj) = ((des(ii, jj) - mixo(ii)) * 0.6 / (maxo(ii) - mixo(ii))) + 0.2
   'Sheet1.Cells(2 + jj, 6) = des(1, jj)
```

```
 Next jj
Next ii
End Sub

Sub TrainingProcess()
'generated initial weight value (Membangkitkan Nilai Weight)
   'r = Val(Right$(Time$, 2))
   'Randomize r

   'Identifikasi nilai Weight
   TW = 1
   For ii = 1 To nl
     For kk = 1 To nn(ii)
       For jj = 1 To nn(ii - 1)
          w(ii - 1, jj, kk) = Sheet1.Cells(2 + TW, 9)
          TW = TW + 1
       Next jj
     Next kk
   Next ii

'Start Proses Iteration
   itend = iterasi
   ite = 0
 For iii = 1 To itend
   erss = 0
   For ii = 2 To nl
      For kk = 1 To nn(ii)
         For jj = 1 To nn(ii - 1)
           dwe(ii - 1, jj, kk) = 0
           dwes(ii - 1, jj, kk) = 0
           dw2s(ii - 1, jj, kk) = 0
           dw2(ii - 1, jj, kk) = 0
         Next jj
      Next kk
   Next ii
   'every case
   For i = 1 To ncase
      For jj = 1 To nn(1)
       X(1, jj) = xinp(jj, i)
      Next jj
     'forward (calculating output of each PE)
     For ii = 2 To nl
       For kk = 1 To nn(ii)
          u(ii, kk) = 0
          For jj = 1 To nn(ii - 1)
             u(ii, kk) = u(ii, kk) + w(ii - 1, jj, kk) * X(ii - 1, jj)
          Next jj
          X(ii, kk) = 1 / (1 + Temp * Exp(-u(ii, kk)))
        Next kk
     Next ii
     'Backward of nlth layer
     For ii = 1 To nn(nl)
       Err2 = des(ii, i) - X(nl, ii)
       d(nl - 1, ii) = Err2 * Temp * Exp(-u(nl, ii)) / (1 + Exp(-u(nl, ii))) ^ 2
       If Err2 > ep Then ep = Abs(Err2)
     Next ii
     'Backward for hidden layer
     For ii = nl - 2 To 1 Step -1
      For kk = 1 To nn(ii + 1)
        d(ii, kk) = 0
        For jj = 1 To nn(ii + 2)
           d(ii, kk) = d(ii, kk) + w(ii + 1, kk, jj) * d(ii + 1, jj)
        Next jj
        d(ii, kk) = d(ii, kk) * Temp * Exp(-u(ii + 1, kk)) / (1 + Exp(-u(ii + 1, kk))) ^ 2
```

```
      Next kk
    Next ii
    'summation of weight value error
    For ii = 2 To nl
      For kk = 1 To nn(ii)
        For jj = 1 To nn(ii - 1)
          dw(ii - 1, jj, kk) = d(ii - 1, kk) * X(ii - 1, jj)
          dwe(ii - 1, jj, kk) = dwe(ii - 1, jj, kk) + dw(ii - 1, jj, kk)
        Next jj
      Next kk
    Next ii
    ersum(i) = 0
    For ii = 0 To nn(nl) - 1
      cal(ii + 1, i) = X(nl, ii + 1)
      er(ii + 1, i) = des(ii + 1, i) - X(nl, ii + 1)
      ersum(i) = ersum(i) + er(ii + 1, i) ^ 2
      If iii = itend Then Sheet1.Cells(2 + i, 7 + (ii * 2)) = (X(nl, ii + 1) - 0.2) * (maxo(ii + 1) - mixo(ii +
1)) / 0.6 + mixo(ii + 1)
    Next ii

   erss = erss + ersum(i)
   Next i
   'Correction of weight value
    For ii = 2 To nl
      For kk = 1 To nn(ii)
        For jj = 1 To nn(ii - 1)
          dwes(ii - 1, jj, kk) = dwes(ii - 1, jj, kk) + dwe(ii - 1, jj, kk)
          'dw2s(ii - 1, jj, kk) = dw2s(ii - 1, jj, kk) + dw2(ii - 1, jj, kk)
          dw2(ii - 1, jj, kk) = dwe(ii - 1, jj, kk)
        Next jj
      Next kk
    Next ii
    npemb = Int(ncase / 4)
    For ii = 2 To nl
      For kk = 1 To nn(ii)
        For jj = 1 To nn(ii - 1)
          w(ii - 1, jj, kk) = w(ii - 1, jj, kk) + Eta * dwes(ii - 1, jj, kk) / npemb + Alpha * dw2s(ii - 1, jj, kk) /
npemb
          dw2s(ii - 1, jj, kk) = dwes(ii - 1, jj, kk)
        Next jj
      Next kk
    Next ii
    erx = erss / nn(nl) / ncase
    delta = erx - ers
    ers = erx
    AdjAp = ep / 0.5
    If AdjAp > 1 Then Temp = 1 / AdjAp  'adjusted gain parameter
    If AdjAp <= 1 Then Temp = 1         'adjusted gain parameter
    Sheet1.Cells(11, 2) = iii
    Sheet1.Cells(12, 2) = delta
    Sheet1.Cells(13, 2) = ers
    Sheet4.Cells(2 + iii, 1) = iii
    Sheet4.Cells(2 + iii, 2) = ers
    ite = ite + 1
    ep = 0
Next iii
'Display Pembobot
 TW = 1
 For ii = 2 To nl
   For kk = 1 To nn(ii)
      For jj = 1 To nn(ii - 1)
        Sheet1.Cells(2 + TW, 10) = w(ii - 1, jj, kk)
        TW = TW + 1
      Next jj
```

```
   Next kk
 Next ii
End Sub

Sub Result()
'Display output data
For ii = 0 To (nn(nl) - 1)
 For jj = 1 To ncase
   Sheet1.Cells(2 + jj, 5) = jj
   Sheet1.Cells(2 + jj, 6 + (ii * 2)) = Sheet2.Cells(jj + 6, 2 + ii)
 Next jj
Next ii
Msg = "Training Process Done": Response = MsgBox(Msg, Style, Title, Help, Ctxt)
End Sub

Sub Validation()
Eta = Sheet1.Cells(2, 2)
Alpha = Sheet1.Cells(3, 2)
Temp = Sheet1.Cells(4, 2)
iterasi = Sheet1.Cells(5, 2)
nl = Sheet1.Cells(6, 2)
ni = Sheet1.Cells(7, 2)
nh = Sheet1.Cells(8, 2)
no = Sheet1.Cells(9, 2)

For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i

'Read Weights
 TW = 1
   For ii = 1 To nl
     For kk = 1 To nn(ii)
       For jj = 1 To nn(ii - 1)
          w(ii - 1, jj, kk) = Sheet1.Cells(2 + TW, 10)
          TW = TW + 1
       Next jj
     Next kk
   Next ii

ncase = Sheet3.Cells(2, 2)
For ii = 1 To ncase
 'Identifikasi Parameter Output (no kolom pertama)
    For jj = 1 To no 'nn(nl)
     des(jj, ii) = Sheet3.Cells(ii + 6, jj + 1)
    Next jj
 'Identifikasi Parameter Input (ni kolom selanjutnya)
    For jj = 1 To ni 'nn(1)
     xinp(jj, ii) = Sheet3.Cells(ii + 6, jj + 1 + no)
    Next jj
Next ii
'Display output
 For ii = 0 To (nn(nl) - 1)
  For jj = 1 To ncase
   Sheet1.Cells(2 + jj, 11) = jj
   Sheet1.Cells(2 + jj, 12) = Sheet3.Cells(jj + 6, 2 + ii)
  Next jj
 Next ii

For ii = 1 To nn(1)
     For jj = 1 To ncase
      xinp(ii, jj) = (xinp(ii, jj) - mixi(ii)) / (maxi(ii) - mixi(ii))
```

```
    Next jj
  Next ii
  For ii = 1 To nn(nl)
   For jj = 1 To ncase
      des(ii, jj) = ((des(ii, jj) - mixo(ii)) * 0.6 / (maxo(ii) - mixo(ii))) + 0.2
    Next jj
  Next ii
  'every case
  For i = 1 To ncase
     For jj = 1 To nn(1)
      X(1, jj) = xinp(jj, i)
     Next jj
    'forward (calculating output of each PE)
    For ii = 2 To nl
      For kk = 1 To nn(ii)
         u(ii, kk) = 0
         For jj = 1 To nn(ii - 1)
            u(ii, kk) = u(ii, kk) + w(ii - 1, jj, kk) * X(ii - 1, jj)
         Next jj
         X(ii, kk) = 1 / (1 + Temp * Exp(-u(ii, kk)))
         Next kk
     Next ii

     For ii = nl To nl
      For kk = 0 To nn(nl) - 1
       hsl(kk + 1, i) = (X(ii, kk + 1) - 0.2) * (maxo(kk + 1) - mixo(kk + 1)) / 0.6 + mixo(kk + 1)
       Sheet1.Cells(2 + i, 13) = hsl(kk + 1, i)
      Next kk
     Next ii
    Next i
End Sub
```

Appendix 5. Source code of GA model in visual basic language

```
'Author: Chusnul Arif
'Date: 12 December 2012
'Organization: Dept. of Global Agricultural Sciences, the University of Tokyo and Dept. of Civil and
Environmental Engineering, Bogor Agricultural University
'Corresponding author: chusnul_arif[at]ipb.ac.id or chusnul_ar[at]yahoo.com
'Website: http://chusnul_arif.staff.ipb.ac.id/

'GA Public
Const Parameter = 3 '(0..2=3 parameter)
Dim individu1(100), individuparameter1(100, 100), cromosom(100, 100, 100), normalisasi(100,
100)
Dim individuparameter2(100, 100), cromosomdesimal(100, 100, 100)
Dim Max(100), Min(100), Fitness(100)
Dim Bb(100), Bb1(100), ko(100)
Dim Cromosomseleksi(100, 100, 100), cromosombaru(100, 100, 100)
Dim ParameterMoisture(100, 100)
Public generationmax, population, Cromsmax, Seleksi, Terseleksi, mutasi
Public fitgenerasi, fitterjelek, fitrata
Public maxkali, kali, aaa, bbb
'ANN public
Public ni, no, nh, ncase
Public Eta, Alpha, Temp, iterasi, nl
Public itend, ite, erss, Err2
Public xinp(100, 1000) As Single
Public des(100, 1000) As Single
Public nn(5) As Integer
Public maxi(1000) As Single
Public maxo(1000) As Single
Public mixi(1000) As Single
Public mixo(1000) As Single
Public w(5, 1000, 1000) As Double
Public u(5, 1000) As Single
Public X(5, 1000) As Single
Public hsl(1000, 1000) As Single
Public MaxYield, MinYield, MaxWP, MinWP, Precipitation
Public SM1, SM2, SM3, SM4
Public PH, TH, Yield, Irri, WP

Sub ReadInput()
generationmax = Sheet1.Cells(2, 2) 'Generation number
population = Sheet1.Cells(3, 2) 'Population number
Cromsmax = Sheet1.Cells(4, 2) 'Number of cromosom
Seleksi = (1 / 100) * Sheet1.Cells(5, 2) 'Crossover rate
Terseleksi = Round(population * Seleksi)
If (Terseleksi Mod 2) = 1 Then Terseleksi = Terseleksi - 1
mutasi = (1 / 100) * Sheet1.Cells(6, 2)
For i = 0 To Parameter
 Max(i) = Sheet1.Cells(8 + i, 2)
 Min(i) = Sheet1.Cells(8 + i, 3)
Next i
MaxYield = Sheet1.Cells(26, 2)
MinYield = Sheet1.Cells(26, 3)
MaxWP = Sheet1.Cells(27, 2)
MinWP = Sheet1.Cells(27, 3)
Precipitation = Sheet1.Cells(31, 2)
End Sub

Sub Pembangkitacak()
Randomize
 For i = 1 To population
```

```
  individu1(i) = ""
   For j = 0 To Parameter
    individuparameter1(i, j) = ""
     For k = 1 To Cromsmax
       r = Rnd
       If r < 0.6 Then cromosom(i, j, k) = "[0]" Else cromosom(i, j, k) = "1"
       individuparameter1(i, j) = individuparameter1(i, j) + cromosom(i, j, k)
      Next k
     individu1(i) = individu1(i) + individuparameter1(i, j)
    Next j
    'Sheet1.Cells(2 + i, 16) = individu1(i)
  Next i
End Sub
Sub Desimal()
For i = 1 To population
   For j = 0 To Parameter
     individuparameter2(i, j) = 0
     maxkali = 0
     For k = 1 To Cromsmax
       kali = XpY(2, Cromsmax - k)
       If cromosom(i, j, k) = "[0]" Then cromosomdesimal(i, j, k) = 0 Else cromosomdesimal(i, j, k) = 1
       individuparameter2(i, j) = individuparameter2(i, j) + kali * cromosomdesimal(i, j, k)
       maxkali = maxkali + kali * 1
      Next k
      koreksi = 1
      normalisasi(i, j) = (individuparameter2(i, j) / maxkali) * (koreksi * Max(j) - Min(j)) + Min(j)
      'Sheet1.Cells(2 + i, 17 + j) = normalisasi(i, j)
    Next j
  Next i
End Sub

Sub FungsiFitness()
 For iii = 1 To population
   SM1 = normalisasi(iii, 0)
   SM2 = normalisasi(iii, 1)
   SM3 = normalisasi(iii, 2)
   SM4 = normalisasi(iii, 3)
   PH = ANNPH(SM1, SM2, SM3, SM4)
   TH = ANNTH(SM1, SM2, SM3, SM4)
   Yield = GrainYield(PH, TH)
   Irri = Irrigation(SM1, SM2, SM3, SM4)
   WP = WaterProductivity(Yield, Irri, Precipitation)
   YieldNormal = (Yield - MinYield) / (MaxYield - MinYield)
   WPNormal = (WP - MinWP) / (MaxWP - MinWP)
   Fitness(iii) = ObjectiveF(YieldNormal, WPNormal)
 Next iii
End Sub
Sub Pengurutan()
For i = 1 To population
 For j = 1 To population
  If Fitness(i) > Fitness(j) Then
    Fit = Fitness(i): Fitness(i) = Fitness(j): Fitness(j) = Fit
     For k = 0 To Parameter
       Bb(k) = individuparameter1(i, k): individuparameter1(i, k) = individuparameter1(j, k):
individuparameter1(j, k) = Bb(k)
       Bb1(k) = individuparameter2(i, k): individuparameter2(i, k) = individuparameter2(j, k):
individuparameter2(j, k) = Bb1(k)
      For ii = 1 To Cromsmax
       ko(ii) = cromosom(i, k, ii): cromosom(i, k, ii) = cromosom(j, k, ii): cromosom(j, k, ii) = ko(ii)
      Next ii
     Next k
  End If
 Next j
Next i
```

```
End Sub

Sub Pemilihanindividu()
For i = 1 To Terseleksi
  For j = 0 To Parameter
   individuparameter1(i, j) = ""
   For k = 1 To Cromsmax
    Cromosomseleksi(i, j, k) = cromosom(i, j, k)
    individuparameter1(i, j) = individuparameter1(i, j) + Cromosomseleksi(i, j, k)
   Next k
  Next j
 Next i
End Sub
Sub crossover()
 For i = 1 + Round(population / 2) To Round(population / 2) + Round(Terseleksi / 2)
     r = Rnd
     rb = 3
     ind1 = (2 * i) - 1
     ind2 = 2 * i
     in1 = ind1 - population
     in2 = ind2 - population
     For j = 0 To Parameter
       individuparameter1(ind1, j) = ""
       individuparameter1(ind2, j) = ""
       For k = 1 To Cromsmax
         If k <= rb Then
           cromosombaru(ind1, j, k) = Cromosomseleksi(in1, j, k)
           individuparameter1(ind1, j) = individuparameter1(ind1, j) + cromosombaru(ind1, j, k)
         Else
           cromosombaru(ind1, j, k) = Cromosomseleksi(in2, j, k)
           individuparameter1(ind1, j) = individuparameter1(ind1, j) + cromosombaru(ind1, j, k)
         End If
         If k <= rb Then
           cromosombaru(ind2, j, k) = Cromosomseleksi(in2, j, k)
           individuparameter1(ind2, j) = individuparameter1(ind2, j) + cromosombaru(ind2, j, k)
        Else
          cromosombaru(ind2, j, k) = Cromosomseleksi(in1, j, k)
          individuparameter1(ind2, j) = individuparameter1(ind2, j) + cromosombaru(ind2, j, k)
        End If
        cromosom(ind1, j, k) = cromosombaru(ind1, j, k)
        cromosom(ind2, j, k) = cromosombaru(ind2, j, k)
      Next k
   Next j
 Next i
End Sub

Sub prosmutasi()
 For i = 1 + Round(population / 2) To Round(population / 2) + Round(Terseleksi / 2)
     ind1 = (2 * i) - 1
     ind2 = 2 * i
     For j = 0 To Parameter
       individuparameter1(ind1, j) = ""
       individuparameter1(ind2, j) = ""
     For k = 1 To Cromsmax
     If (Rnd < mutasi) And (cromosom(ind1, j, k) = "[0]") Then cromosom(ind1, j, k) = "1"
     If (Rnd < mutasi) And (cromosom(ind1, j, k) = "1") Then cromosom(ind1, j, k) = "[0]"
     If (Rnd < mutasi) And (cromosom(ind2, j, k) = "[0]") Then cromosom(ind2, j, k) = "1"
     If (Rnd < mutasi) And (cromosom(ind2, j, k) = "1") Then cromosom(ind2, j, k) = "[0]"
     individuparameter1(ind1, j) = individuparameter1(ind1, j) + cromosom(ind1, j, k)
     individuparameter1(ind2, j) = individuparameter1(ind2, j) + cromosom(ind2, j, k)
    Next k
   Next j
 Next i
End Sub
```

```
Sub desimal1()
For i = 1 + Round(population / 2) To Round(population / 2) + Round(Terseleksi / 2)
  ind1 = (2 * i) - 1
  ind2 = 2 * i
   For j = 0 To Parameter
     individuparameter2(ind1, j) = 0
     individuparameter2(ind2, j) = 0
     maxkali = 0
     For k = 1 To Cromsmax
       kali = XpY(2, Cromsmax - k)
       If cromosom(ind1, j, k) = "[0]" Then cromosomdesimal(ind1, j, k) = 0 Else
cromosomdesimal(ind1, j, k) = 1
       If cromosom(ind2, j, k) = "[0]" Then cromosomdesimal(ind2, j, k) = 0 Else
cromosomdesimal(ind2, j, k) = 1
       individuparameter2(ind1, j) = individuparameter2(ind1, j) + kali * cromosomdesimal(ind1, j, k)
       individuparameter2(ind2, j) = individuparameter2(ind2, j) + kali * cromosomdesimal(ind2, j, k)
       maxkali = maxkali + kali * 1
      Next k
      koreksi = 1
      normalisasi(ind1, j) = (individuparameter2(ind1, j) / maxkali) * (koreksi * Max(j) - Min(j)) + Min(j)
      normalisasi(ind2, j) = (individuparameter2(ind2, j) / maxkali) * (koreksi * Max(j) - Min(j)) + Min(j)
      'Sheet1.Cells(37 + i, 9 + j) = normalisasi(i, j)
  Next j
 Next i
End Sub

Sub FungsiFitness1()
 For iii = 1 To population + Terseleksi
  For j = 0 To Parameter
   normalisasi(iii, j) = (individuparameter2(iii, j) / maxkali) * (1 * Max(j) - Min(j)) + Min(j)
  Next j
   SM1 = normalisasi(iii, 0)
   SM2 = normalisasi(iii, 1)
   SM3 = normalisasi(iii, 2)
   SM4 = normalisasi(iii, 3)
   PH = ANNPH(SM1, SM2, SM3, SM4)
   TH = ANNTH(SM1, SM2, SM3, SM4)
   Yield = GrainYield(PH, TH)
   Irri = Irrigation(SM1, SM2, SM3, SM4)
   WP = WaterProductivity(Yield, Irri, Precipitation)
   YieldNormal = (Yield - MinYield) / (MaxYield - MinYield)
   WPNormal = (WP - MinWP) / (MaxWP - MinWP)
   Fitness(iii) = ObjectiveF(YieldNormal, WPNormal)
 Next iii
End Sub

Sub Pengurutan1()
For i = 1 To population + Terseleksi
 For j = 1 To population + Terseleksi
  If Fitness(i) > Fitness(j) Then
    Fit = Fitness(i): Fitness(i) = Fitness(j): Fitness(j) = Fit
     For k = 0 To Parameter
       Bb(k) = individuparameter1(i, k): individuparameter1(i, k) = individuparameter1(j, k):
individuparameter1(j, k) = Bb(k)
       Bb1(k) = individuparameter2(i, k): individuparameter2(i, k) = individuparameter2(j, k):
individuparameter2(j, k) = Bb1(k)
      For ii = 1 To Cromsmax
       ko(ii) = cromosom(i, k, ii): cromosom(i, k, ii) = cromosom(j, k, ii): cromosom(j, k, ii) = ko(ii)
      Next ii
     Next k
  End If
  'Sheet1.Cells(1 + j, 11) = Fitness(j)
 Next j
```

```
Next i
End Sub

Sub Pengurutan2()
For i = 1 To population
 For j = 1 To population
  If Fitness(i) > Fitness(j) Then
    Fit = Fitness(i): Fitness(i) = Fitness(j): Fitness(j) = Fit
     For k = 0 To Parameter
       Bb(k) = individuparameter1(i, k): individuparameter1(i, k) = individuparameter1(j, k):
individuparameter1(j, k) = Bb(k)
       Bb1(k) = individuparameter2(i, k): individuparameter2(i, k) = individuparameter2(j, k):
individuparameter2(j, k) = Bb1(k)
      For ii = 1 To Cromsmax
       ko(ii) = cromosom(i, k, ii): cromosom(i, k, ii) = cromosom(j, k, ii): cromosom(j, k, ii) = ko(ii)
      Next ii
     Next k
  End If
  'Sheet1.Cells(1 + j, 12) = Fitness(j)
 Next j
Next i
End Sub

Sub statistik()
 sumfitness = 0
    For i = 1 To population
      sumfitness = sumfitness + Fitness(i)
    Next i
    fitgenerasi = Fitness(1)
    fitterjelek = Fitness(population)
    fitrata = sumfitness / population
    'Sheet1.Cells(2, 13) = fitgenerasi
    'Sheet1.Cells(3, 13) = fitterjelek
    'Sheet1.Cells(4, 13) = fitrata
End Sub

Sub hasil(gen)
 Sheet1.Cells(2 + gen, 5) = gen
 Sheet1.Cells(2 + gen, 6) = fitgenerasi
 Sheet1.Cells(2 + gen, 7) = fitterjelek
 Sheet1.Cells(2 + gen, 8) = fitrata
 Sheet1.Cells(2 + gen, 11) = normalisasi(1, 0)
 Sheet1.Cells(2 + gen, 12) = normalisasi(1, 1)
 Sheet1.Cells(2 + gen, 13) = normalisasi(1, 2)
 Sheet1.Cells(2 + gen, 14) = normalisasi(1, 3)
 SM1 = normalisasi(1, 0)
 SM2 = normalisasi(1, 1)
 SM3 = normalisasi(1, 2)
 SM4 = normalisasi(1, 3)
   PH = ANNPH(SM1, SM2, SM3, SM4)
   TH = ANNTH(SM1, SM2, SM3, SM4)
   Yield = GrainYield(PH, TH)
   Irri = Irrigation(SM1, SM2, SM3, SM4)
   WP = WaterProductivity(Yield, Irri, Precipitation)
 Sheet1.Cells(2 + gen, 9) = Yield
 Sheet1.Cells(2 + gen, 10) = WP
 Sheet1.Cells(17, 2) = fitgenerasi
 Sheet1.Cells(18, 2) = normalisasi(1, 0)
 Sheet1.Cells(19, 2) = normalisasi(1, 1)
 Sheet1.Cells(20, 2) = normalisasi(1, 2)
 Sheet1.Cells(21, 2) = normalisasi(1, 3)
 Sheet1.Cells(23, 2) = Yield
 Sheet1.Cells(24, 2) = WP
 Sheet1.Cells(33, 2) = Irri
```

```
 Sheet1.Cells(34, 2) = (342.6 - Irri) / 342.6
 Sheet1.Cells(35, 2) = (Yield - 10) / 10
End Sub

Function GrainYield(a, b)
 GrainYield = a * 0.10736297 + b * 0.323426 - 13.03 'by multiple regression
End Function
Function Irrigation(a, b, c, d)
 Irrigation = a * 0 + b * (-361.78) + c * (408.28) + d * 346.7 + 168.62 'by multiple regression
End Function
Function WaterProductivity(a, b, c)
 WaterProductivity = (a / (b + c)) * 100
End Function
Function ObjectiveF(a, b)
 Coeff1 = Sheet1.Cells(29, 2)
 Coeff2 = Sheet1.Cells(30, 2)
 ObjectiveF = a * Coeff1 + b * Coeff2
End Function
Function XpY(X, Y)
 If X = 0 Then XpY = 0 Else XpY = Exp(Y * Log(X))
End Function

Function ANNPH(a, b, c, d)
ncase = 1
Eta = Sheet2.Cells(2, 2)
Alpha = Sheet2.Cells(3, 2)
Temp = Sheet2.Cells(4, 2)
nl = Sheet2.Cells(5, 2)
ni = Sheet2.Cells(6, 2)
nh = Sheet2.Cells(7, 2)
no = Sheet2.Cells(8, 2)

For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i

For ii = 1 To ncase
 'Identifikasi Parameter Input (ni kolom selanjutnya)
    For jj = 1 To ni 'nn(1)
     xinp(1, ii) = a
     xinp(2, ii) = b
     xinp(3, ii) = c
     xinp(4, ii) = d
    Next jj
Next ii

'identify maximum and minimum input
For ii = 1 To ni
 maxi(ii) = Sheet2.Cells(1 + ii, 7)
 mixi(ii) = Sheet2.Cells(1 + ii, 8)
Next ii

'identify maximum and minimum output
For ii = 1 To no
 maxo(ii) = Sheet2.Cells(5 + ii, 7)
 mixo(ii) = Sheet2.Cells(5 + ii, 8)
Next ii

'Read Weights
 TW = 1
   For ii = 1 To nl
     For kk = 1 To nn(ii)
```

```
      For jj = 1 To nn(ii - 1)
         w(ii - 1, jj, kk) = Sheet2.Cells(1 + TW, 5)
         TW = TW + 1
      Next jj
    Next kk
  Next ii

'normalization
  For ii = 1 To nn(1)
    For jj = 1 To ncase
     xinp(ii, jj) = (xinp(ii, jj) - mixi(ii)) / (maxi(ii) - mixi(ii))
    Next jj
  Next ii

  For ii = 1 To nn(nl)
   For jj = 1 To ncase
      des(ii, jj) = ((des(ii, jj) - mixo(ii)) * 0.6 / (maxo(ii) - mixo(ii))) + 0.2
    Next jj
  Next ii

  'every case
  For i = 1 To ncase
     For jj = 1 To nn(1)
      X(1, jj) = xinp(jj, i)
     Next jj
    'forward (calculating output of each PE)
    For ii = 2 To nl
      For kk = 1 To nn(ii)
         u(ii, kk) = 0
         For jj = 1 To nn(ii - 1)
            u(ii, kk) = u(ii, kk) + w(ii - 1, jj, kk) * X(ii - 1, jj)
         Next jj
         X(ii, kk) = 1 / (1 + Temp * Exp(-u(ii, kk)))
         Next kk
     Next ii

     For ii = nl To nl
      For kk = 0 To nn(nl) - 1
       hsl(kk + 1, i) = (X(ii, kk + 1) - 0.2) * (maxo(kk + 1) - mixo(kk + 1)) / 0.6 + mixo(kk + 1)
       ANNPH = hsl(0 + 1, i)
      Next kk
     Next ii
    Next i
End Function

Function ANNTH(a, b, c, d)
ncase = 1
Eta = Sheet2.Cells(2, 2)
Alpha = Sheet2.Cells(3, 2)
Temp = Sheet2.Cells(4, 2)
nl = Sheet2.Cells(5, 2)
ni = Sheet2.Cells(6, 2)
nh = Sheet2.Cells(7, 2)
no = Sheet2.Cells(8, 2)

For i = 1 To nl
 nn(1) = ni   'Identifikasi Jumlah Unit Tiap Layer
 nn(2) = nh
 nn(3) = no
Next i

For ii = 1 To ncase
 'Identifikasi Parameter Input (ni kolom selanjutnya)
   For jj = 1 To ni 'nn(1)
```

```
    xinp(1, ii) = a
    xinp(2, ii) = b
    xinp(3, ii) = c
    xinp(4, ii) = d
   Next jj
Next ii

'identify maximum and minimum input
For ii = 1 To ni
 maxi(ii) = Sheet2.Cells(1 + ii, 7)
 mixi(ii) = Sheet2.Cells(1 + ii, 8)
Next ii

'identify maximum and minimum output
For ii = 1 To no
 maxo(ii) = Sheet2.Cells(5 + ii, 7)
 mixo(ii) = Sheet2.Cells(5 + ii, 8)
Next ii

'Read Weights
 TW = 1
  For ii = 1 To nl
    For kk = 1 To nn(ii)
      For jj = 1 To nn(ii - 1)
         w(ii - 1, jj, kk) = Sheet2.Cells(1 + TW, 5)
         TW = TW + 1
      Next jj
    Next kk
  Next ii

'normalization
 For ii = 1 To nn(1)
    For jj = 1 To ncase
     xinp(ii, jj) = (xinp(ii, jj) - mixi(ii)) / (maxi(ii) - mixi(ii))
    Next jj
  Next ii

  For ii = 1 To nn(nl)
   For jj = 1 To ncase
      des(ii, jj) = ((des(ii, jj) - mixo(ii)) * 0.6 / (maxo(ii) - mixo(ii))) + 0.2
    Next jj
  Next ii

  'every case
  For i = 1 To ncase
     For jj = 1 To nn(1)
      X(1, jj) = xinp(jj, i)
     Next jj
    'forward (calculating output of each PE)
    For ii = 2 To nl
      For kk = 1 To nn(ii)
         u(ii, kk) = 0
         For jj = 1 To nn(ii - 1)
            u(ii, kk) = u(ii, kk) + w(ii - 1, jj, kk) * X(ii - 1, jj)
         Next jj
         X(ii, kk) = 1 / (1 + Temp * Exp(-u(ii, kk)))
         Next kk
     Next ii

     For ii = nl To nl
      For kk = 0 To nn(nl) - 1
       hsl(kk + 1, i) = (X(ii, kk + 1) - 0.2) * (maxo(kk + 1) - mixo(kk + 1)) / 0.6 + mixo(kk + 1)
       ANNTH = hsl(1 + 1, i)
      Next kk
```

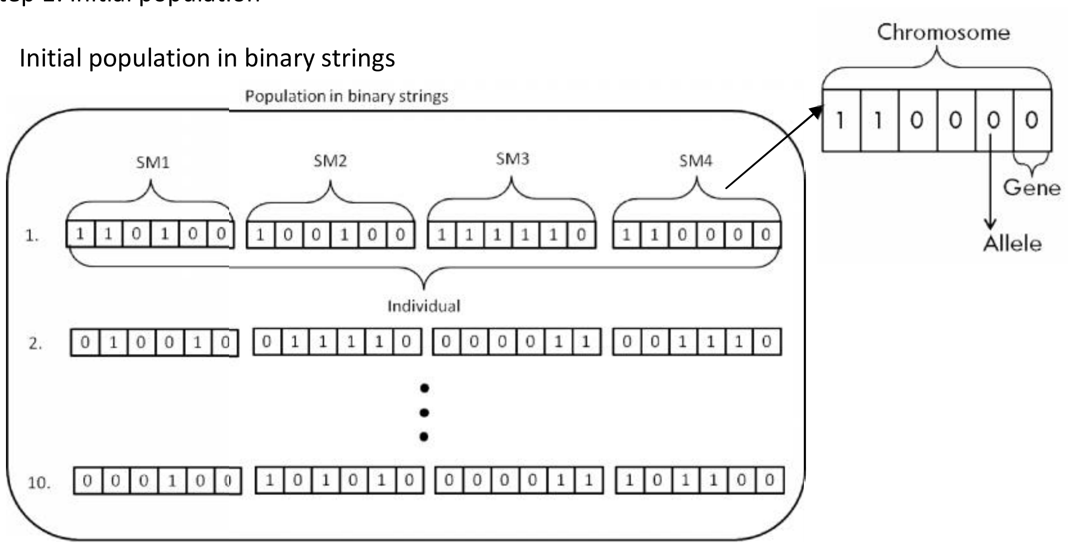
```
        Next ii
      Next i

End Function
```

Appendix 6. The detail process of GA optimization

K = 0

Step 1: Initial population

- Initial population in binary strings



- Initial population in decimal values

Individual	Decimal (cm3/cm3)			
	SM1	SM2	SM3	SM4
1	0.609	0.591	0.516	0.486
2	0.596	0.588	0.514	0.350
3	0.594	0.571	0.456	0.466
4	0.592	0.587	0.489	0.404
5	0.589	0.580	0.503	0.486
6	0.611	0.565	0.459	0.434
7	0.603	0.564	0.498	0.473
8	0.589	0.576	0.468	0.365
9	0.600	0.563	0.494	0.402
10	0.590	0.570	0.457	0.360

Step-2: Estimate plant height, tillers/hill, yield and water productivity

Individual	Parameters			
	Plant height	Tillers/hill	Yield	Water productivity
1	118.63	28.85	9.04	1.02
2	118.98	30.98	9.76	1.16
3	112.85	27.25	7.90	0.92
4	116.48	29.53	9.03	1.07
5	112.43	26.46	7.60	0.86
6	118.69	29.81	9.36	1.10
7	117.04	28.32	8.69	0.98
8	114.86	29.81	8.94	1.08
9	119.30	30.22	9.55	1.11
10	114.41	29.80	8.89	1.08

Step 3: Calculate fitness function

Individual	Fitness
1	0.52
2	0.61
3	0.43
4	0.54
5	0.39
6	0.56
7	0.49
8	0.54
9	0.58
10	0.53

Step-4: Selection

Before process selection

Individual	Fitness
1	0.52
2	0.61
3	0.43
4	0.54
5	0.39
6	0.56
7	0.49
8	0.54
9	0.58
10	0.53

Individuals are selected

after process selection

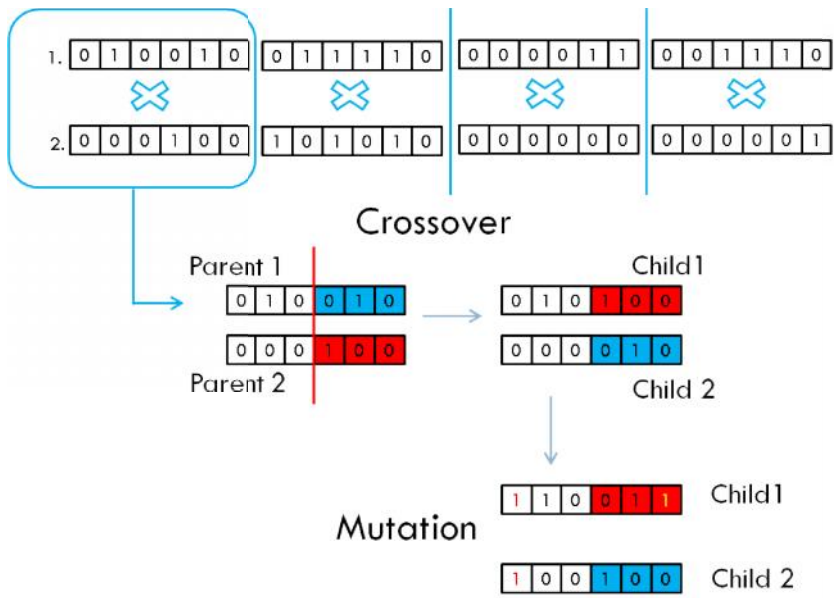
Individual	Fitness
1	0.61
2	0.58
3	0.56
4	0.54
5	0.53
6	0.53
7	0.52
8	0.49
9	0.43
10	0.39

Selected

Eliminated

Step-5: Crossover and mutation

The selected individuals are to be "parent" that will be crossed each other. Crossover will be performed between each chromosome. For example, chromosome of SM1 in first individual will be crossed to the chromosome of SM1 in the second individual. From this process, new "child" will be created. Then some "alleles" of each chromosome will be mutated, from "1" to be "0" and *vice versa*.



Step-6: new population

New and old individuals are compared

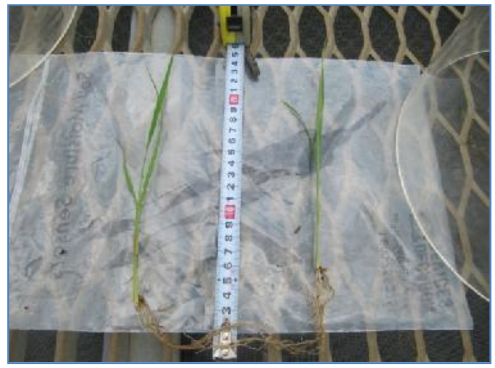
Elitism strategy was carried out to create new population

K = 1

Step-2 to step-6 are repeated until K=100.

Appendix 7. Documentation during field experiment in Japan

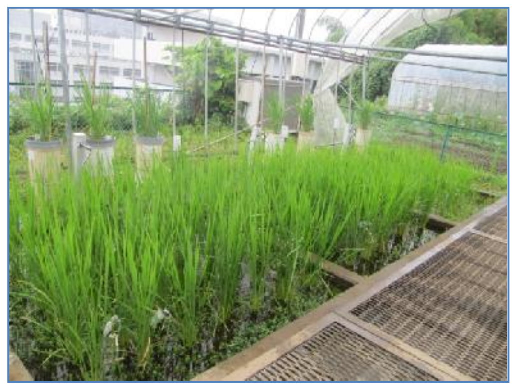
Seedlings

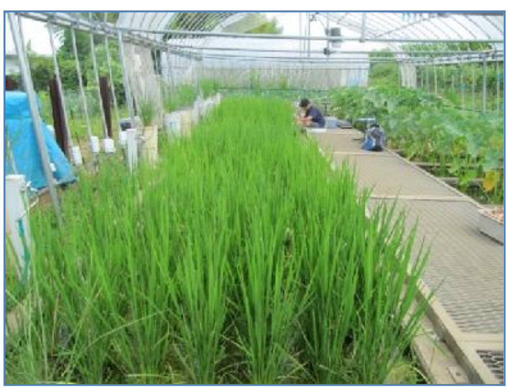


Planting

Gas sampling

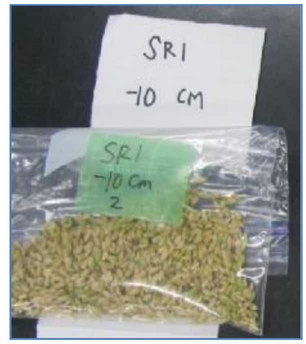
Plant growing





Harvesting


SRI
0 CM
SRI
0CM
2

SRI
-5 CM
SRI
-5 CM
2

SRI
-10 CM
SRI
-10 Cm
2

SRI
FLOODING
SRI
COMBINATION
SRI
DRY

Appendix 8. List of publication papers during the study

A. Journal Papers

1. **Arif C,** Budi Indra Setiawan, Masaru Mizoguchi, Ryoichi Doi. 2012. Estimation of Water Balance Components in Paddy Fields under Non-Flooded Irrigation Regimes by using Excel Solver. Journal of Agronomy vol 11(2):53-59
2. **Arif C,** Budi Indra Setiawan, Hanhan Ahmad Sofiyuddin, Lolly Martina Martief, Masaru Mizoguchi, Ryoichi Doi. 2012. Estimating Crop Coefficient in an Intermittent Irrigation Paddy Field using Excel Solver. Rice Science, Vol. 19 No. 2: 143-152
3. **Arif C,** Masaru Mizoguchi, Budi I Setiawan, Ryoichi Doi. 2012. Estimation of soil moisture in paddy field using Artificial Neural Networks. International Journal of Advanced Research in Artificial Intelligence (IJARAI), Vol. 1, No. 1:17-21, 2012

B. Conferences Papers

1. **Arif C**, Masaru Mizoguchi, Budi Indra Setiawan, Ryoichi Doi. 2013. Optimizing Water Management of System of Rice Intensification for Climate Change Adaptation Strategy Based on Field Monitored Data. GRENE 2nd workshop, 4-6 March 2013, Baguio, Philippine. Oral Presentation
2. **Arif C**, Budi Indra Setiawan, Masaru Mizoguchi, Ryoichi Doi. 2012. Optimizing Non-flooded Irrigation Regime under System of Rice Intensification Crop Management using Genetic Algorithms. PAWEES 2012 International Conference, 27-28 October 2012, Bangkok, Thailand. Oral Presentation
3. **Arif C**, Masaru Mizoguchi, Budi Indra Setiawan, Ryoichi Doi. 2012. Evaluating Alternate Wetting and Drying Irrigation Regimes under System of Rice Intensification Crop Management through Field Monitoring System. Marco Symposium 2012, 24-27 September 2012, Tsukuba, Japan. Poster presentation P1-6:173
4. **Arif C**, Masaru Mizoguchi, Budi Indra Setiawan, Ryoichi Doi. 2012. Application of Neural Networks for Soil Moisture Estimation in Paddy Field

with Limited Meteorological Data. JSIDRE conference 18-20 September 2012, Sapporo, Japan. Poster presentation

5. **Arif C,** Masaru Mizoguchi, Budi Indra Setiawan, Tetsu Ito, Ryoichi Doi. 2012. Field monitoring system for decision support of SRI practice as a climate change adaptation strategy in Indonesia. AgroInformatics 2012 Conference (in Japanese). Tokyo, 16-17 May 2012. Oral presentation
6. **Arif C,** Masaru Mizoguchi, Budi I Setiawan, Ryoichi Doi. 2011. Water Management Evaluation of Alternate Wetting and Drying Irrigation in Paddy Fields by Considering Monitored Soil Moisture. Soil Moisture Workshop 2011, December 2011, Tokyo, Japan. Oral presentation
7. **Arif C,** Budi I Setiawan, Masaru Mizoguchi, Ryoichi Doi**.** 2011**.** Estimation of Water Balance Variables in the SRI Paddy Field by Considering Soil Moisture. PAWEES 2011 International Conference on "Capacity Building for Participatory Irrigation and Environmental Management" 27-28 October, 2011 in Taiwan. Oral presentation
8. **Arif C,** Budi I Setiawan, Masaru Mizoguchi, Ryoichi Doi, Satyanto K Saptomo, Ardiansyah, Tetsu Ito. 2011. Field Network System to Monitor Paddy Fields in the System of Rice Intensification in Indonesia. Presented on CIGR 2011 conference on Sustainable Bioproduction, 19-23 September 2011 in Tokyo. Oral presentation
9. **Arif C,** Hanhan A. Sofiyuddin, Lolly M. Martief**,** Budi I Setiawan, Masaru Mizoguchi and Ryoichi Doi. 2010. Crop Coefficient of Paddy under System of Rice Intensification (SRI) Environment. INWEPF – PAWEES Joint Symposium October 27 – 29, 2010, Jeju Island, Korea. Poster presentation