NAGASAKI UNIVERSITY

GRADUATE SCHOOL OF ENGINEERING

Doctoral Thesis

THE CHANGE OF VEGETATION IN MEKONG DELTA AND ITS EFFECT FOR THE HYDROLOGICAL MECHANISM USING GIS AND REMOTE SENSING

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ABSTRACT

Vietnam is one of the most important countries in producing rice in Asia as well as in the world. The majority of rice is produced in the Mekong Delta which is known as the rice bowl of Vietnam. Annually, it produces approximately a half of the country rice and account for more than 80% amount of rice export. Therefore, information on rice growing areas is vital for crop management and production prediction. This study aimed to mapping rice cropping systems in the Mekong Delta, Vietnam using the Moderate Resolution Imaging Spectroradiometer (MODIS) data. The spatial distribution of rice cropping systems was obtained from classification of the time-series MODIS NDVI 250 m data acquired in 2002, 2005, 2010, and 2015. The data were processed through four main steps: (1) to construct smooth time-series NDVI data using the wavelet transform, (2) to analyze NDVI profiles and select the training patterns, (3) to classify time series NDVI for rice cropping systems by using SVMs, and (4) result verification using the ground truth image and ancillary data.

The results showed that the estimated sowing/heading dates and the ancillary data indicated that the use of smooth time profiles MODIS NDVI 250-m data could be used for detecting phenological dates. These NDVI patterns reflected seasonal changes in crop phenology of rice cropping systems, which was important for understanding the temporal NDVI responses of different rice fields of cropping patterns in the study area. The SVMs was applied to the filtered time-series NDVI data for classification of rice cropping systems in the region. The classification maps for 2015 was compared with the ground truth data. The overall accuracy and Kappa coefficient were 82.5% and 0.73. This study demonstrated merits of using MODIS
data for studying on rice cropping systems, which is important for crop and water management.

In case of mangrove forests, land covers have changed in the Mekong Delta, Vietnam with difficulty for stable and sustainable management in the past three decades. Therein, mangrove has significantly changed during that period due to shrimp culture development rapidly. Therefore, monitoring a spatiotemporal distribution and changes of mangrove is critical for natural resource management. To contribute better management for mangrove and coastlines in the area, the research objectives were: to map the current extent of mangrove in the Ca Mau peninsula from 1989 to 2015, and to identify change of mangrove. The data were processed through four main steps: (1) data pre-processing including atmospheric correction, image normalization, and cloud removal, (2) image classification using the supervised classification approach, (3) accuracy assessment, and (4) change detection analysis.

Validation was made by comparing the classification result with the ground reference data, which yielded agreement with overall accuracy 77.4% and Kappa coefficient of 0.68. The results showed that mangrove has decreased by half (236.07 km$^2$) from 1989 to 1998 due to shrimp culture. At the same time, the area of mix shrimp and mangrove increased by 386.69 km$^2$ (about 88%). However, mangrove and mix mangrove, and shrimp areas have been raised by twice for mangrove and about 11% for mix mangrove and shrimp, respectively, in the second period from 1998 to 2015. These changes of mangrove were affected by two activities: deforestation and replanting or newly formed. The development of aquaculture has been increasing
quite rapidly and in an unplanned way. It also caused environmental and natural resource problems as well as socio-economic aspects. Research results for mangrove mapping and change detection in the study area are capable of providing quantitative information of long-term land-use change for coastal management in the Mekong delta.

In addition, clearing of upstream forests has reportedly changed rainfall-runoff relations, resulting in larger, more frequent floods and an increase in dry season flows, primarily as a result of reservoir construction on tributaries in the Mekong delta, Vietnam. Satellite remote sensing is a promising technique for estimating global and regional evapotranspiration (ET). A simple and accurate method is essential in estimating ET with remote sensing data. Information on long-term water is very important for agriculture and water resource management. Monitoring changes in water resource is thus required for natural resource management in the Mekong delta. The results showed that temperature increased and rainfall decreased while land cover constitution was constant. In this research, evapotranspiration increased during the research period. For a long term water balance, runoff was decreasing due to land cover changed in the Mekong delta and the other manmade factor in the upstream. This was a main cause that directly affected on water resource management. The overall efforts in this study demonstrated the effectiveness of the proposed method used for detecting changes of long-term water resource, improving the ability to capture spatial variability of water demands in the basin. The crisis for agriculture would occur in the Mekong Delta in the future.
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<th>Description</th>
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</thead>
<tbody>
<tr>
<td>BISE</td>
<td>Best Index Slope Extraction</td>
</tr>
<tr>
<td>CDR</td>
<td>Climate Data Record</td>
</tr>
<tr>
<td>CMP</td>
<td>Ca Mau peninsula</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DN</td>
<td>Digital Number</td>
</tr>
<tr>
<td>DOF</td>
<td>Degrees-of-Freedom</td>
</tr>
<tr>
<td>DOY</td>
<td>Day of Year</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform</td>
</tr>
<tr>
<td>ENVI</td>
<td>Environment for Visualizing Images</td>
</tr>
<tr>
<td>EM</td>
<td>Electromagnetic</td>
</tr>
<tr>
<td>EMD</td>
<td>Empirical Mode Decomposition</td>
</tr>
<tr>
<td>ETM+</td>
<td>Enhanced Thematic Mapper plus</td>
</tr>
<tr>
<td>IR</td>
<td>Infrared</td>
</tr>
<tr>
<td>IRRI</td>
<td>International Rice Research Institute</td>
</tr>
<tr>
<td>IUCN</td>
<td>International Union for Conservation of Nature</td>
</tr>
<tr>
<td>JM</td>
<td>Jefferies-Matusita</td>
</tr>
<tr>
<td>LEDAPS</td>
<td>Landsat Ecosystem Disturbance Adaptive Processing System</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalize Different Vegetation Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infrared</td>
</tr>
<tr>
<td>MARD</td>
<td>Ministry of Agriculture and Rural Development</td>
</tr>
<tr>
<td>Acronym</td>
<td>Full Form</td>
</tr>
<tr>
<td>---------</td>
<td>-----------</td>
</tr>
<tr>
<td>MLC</td>
<td>Maximum Likelihood Classification</td>
</tr>
<tr>
<td>MONRE</td>
<td>Ministry of Natural Resources and Environment</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MRA</td>
<td>Multi-Resolution Analysis</td>
</tr>
<tr>
<td>OSH</td>
<td>Optimal Separating Hyper plane</td>
</tr>
<tr>
<td>OLI</td>
<td>Operational Land Imager</td>
</tr>
<tr>
<td>SVMs</td>
<td>Support Vector Machines</td>
</tr>
<tr>
<td>TM</td>
<td>Thematic Mapper</td>
</tr>
<tr>
<td>TOA</td>
<td>Top of Atmosphere</td>
</tr>
<tr>
<td>RBF</td>
<td>Radial Basis Function</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>ROI</td>
<td>Region of Interest</td>
</tr>
<tr>
<td>USA</td>
<td>United State of America</td>
</tr>
<tr>
<td>USGS</td>
<td>United States Geological Survey</td>
</tr>
<tr>
<td>UTM</td>
<td>Universal Transverse Mercator</td>
</tr>
<tr>
<td>WGS84</td>
<td>World Geodetic System 1984</td>
</tr>
</tbody>
</table>
1. INTRODUCTION

1.1. Background

Over the last three decades, the Mekong Delta has undergone drastic changes in hydrology to improve agricultural production (Duong and Cho, 1994; Xuan and Matsui, 1998; Hashimoto, 2001; Minh and Kawaguchi, 2002). New canals and sluices resulted in a complex web of interconnected water bodies that will further be expanded to improve living condition of approximately 16 million inhabitants. The Vietnamese part of the Mekong Delta covers an area of 39000 km$^2$ (of about 6 mi ha of the total Mekong Delta, including Cambodian part) of which 29000 km$^2$ are currently used for agriculture, 6000 km$^2$ for settlements and infrastructures and the remainder being mangrove and melaleuca forests. In 2000, rice production constituted 78% of the land use in the Mekong Delta. Although 60% of the soils in the Mekong Delta are acid sulfate and saline soils, rice production has markedly increased in recent years allowing Vietnam to become the top largest rice exporter of the world (Sanh et al., 1998).

The land in the Mekong Delta is only slightly (2 m) above mean sea level. Approximately 1 mi ha are affected by tidal flooding and 1.7 mi ha by salt water intrusion. The Mekong Delta has experienced devastating floods by water from the Mekong River. These losses could substantially exacerbate under sea level rise. Given the dimension of coastal plains in Asia, sea level rise is likely to become a major challenge to many Asian countries, with Bangladesh being probably the most drastic example on national scale (Warrick and Ahmad, 1996; Ali, 1996).
During recent years, rice crops in this region have been affected by insufficient water for irrigation, deficient soil moisture and encroachment of saltwater during the dry season. This is because the level of the Mekong River falls as the river levels in the region drop and seawater encroaches further into the rice fields. The deficiency in water resource combined with the salinity intrusion has created difficulties for rice cultivation in the region. Besides, saltwater encroached approximately 40 - 60 km further into the rivers of the Mekong Delta’s coastal provinces (VNS, 2007). People living along the rice field embankments were faced with a water deficit for rice production. Leading world agriculturalists have warned that rice production in the region will be reduced even more, because the region is likely to face more water shortages over the next decade (Oryza, 2009).

The rationale for this study is primarily given by the economic significance of rice production. Rice production is affected by global climate change through various pathways. Increasing concentrations of carbon dioxide stimulate photosynthesis, while concomitant global warming may result in heat stress for rice grown in tropical or subtropical climates (Moya et al., 1998). The productivity of rice systems may also be altered by hydrological changes, deriving either from changing precipitation patterns or - as investigated in this regional case study - from higher sea level. On the other hand, rice production itself is a source of greenhouse gases, mainly methane (Wassmann et al., 2000).

In the other parts of the thesis, changes in vegetation was seriously throughout the past decades in the Mekong Delta, especially is mangrove forests in the coastal area. As we all know that, mangrove grows in river deltas, estuarine complexes and coasts...
in the tropical and subtropical regions throughout the world. The total mangrove area accounts for 0.7% of total tropical forests of the world. The largest extent of mangrove is found in Asia (42.0%) followed to Africa (20.0%), North and Central America (15.0%), Oceania (12.0%) and South America (11.0%) (Giri et al., 2011). Therein, Vietnam is estimated to have 1580 km² of mangrove ranking 24 among 118 countries and territories supporting mangrove. It is estimated that the area of mangrove was about 4,000 km² in the 1940s. However, this area has declined dramatically, especially since the 1980s. Much of this loss can be attributed to the conversion of forests into rice fields and, more recently, shrimp ponds (loss of approximately 76.4% of mangrove). Therein, mangrove in the Mekong Delta was covered more than 2,500 km² (Maurand, 1943 cited in Hong and San, 1993) and mainly distributed in Ca Mau peninsula.

In the past three decades, mangrove in the Ca Mau peninsula was reduced due to deforestation for fuel, wood construction, the war, forest fire and other human activities. Especially, mangrove forests have been cleared for shrimp farming in many areas with thousands hectare of mangrove (Hong and San, 1993; Hong, 1995; and Hao, 1999) since the end of 1980s and in the 1990s and/or changed in land used from rice fields to shrimp culture based on the income and economic. It is very difficult for native government to control the change in land use. There were many factors that have affected the mangrove changes of the delta, and the most important factor that was the shrimp culture activities with the high economic returns, resulted of mangrove restructure. The pattern of land uses in the Mekong Delta has been changed significantly over decades. Therefore, monitoring changes in vegetation is thus
becomes increasingly important in the Mekong Delta, especially rice field and mangrove forest area. Policymakers need information on these information of changes based on the results to devise better water management strategies for agricultural and aquaculture development.

1.2. Statement of problem

In the Mekong Delta, land cover plays an important role for suitable development. Therein, agriculture (rice crop) and aquaculture (shrimp farm) are the most important for developing the region.

Rice is the major economic crop in the Mekong Delta in providing livelihoods and employment for majority of rural population in the region. Rice cultivation in this region is heavily dependent on the availability of water. More frequent rainfall deficiencies in recent years have triggered water deficits and negatively affected rice production. Therefore, information on rice growing areas and water resource variability in relation to cropping areas are essential for crop and water management. This information is necessary for policymakers to devise timely development plans that will ensure food security.

For years, this information has been traditionally collected through time-consuming and costly field surveys. Remote sensing has been recognized as an indispensable tool for monitoring vegetation on national, regional and global scales. As the use of high-resolution satellites for crop monitoring is often restricted due to coverage, temporal resolution and cost limitations, the low-resolution MODIS satellite appears to be a good candidate for providing data for this purpose. This is because of the fact
that MODIS satellite can provide data regular basic with a high-frequency revisit capability and wide coverage. As in many parts of the study area, rice cropping practices have recently changed due to the improvement of flood control and water management systems, there is thus a need to develop a robust method for mapping and updating information of rice cropping systems in the region. An analysis of the spatial distribution for rice cropping systems was also necessarily implemented in respect to effective monitoring of rice production area and water management practices.

Besides, the availability of the earth observation satellite data like Landsat data is useful for change detection applications. The distribution and abundance of mangrove in different regions of the world have been assessed with a variety of techniques. Based on the importance and vulnerable of mangrove ecosystems faced, many studies on mangrove have been conducted to solve these issues in different scales, long-term monitoring and detecting mangrove by using remote sensing techniques (Blasco et al., 2001; Everitt et al., 2008; Giri et al., 2007; Green, 1998; Seto and Fragkias., 2007; and Vaiphasa et al., 2006). In addition, change detection is a powerful tool to visualize, to measure, and better to understand a trend in mangrove ecosystems. It enables the evaluation changes over a long period of time as well as the identification of sudden changes due to natural or dramatic anthropogenic impacts (e.g. tsunami destruction or conversion to shrimp farms).

Thus, distribution, condition, and increase or decrease were the measured features used in the change-detection applications of mangrove. Monitoring change in mangrove was adopted by many researchers throughout the world (Giri et al., 2011;
Giri et al., 2007; Ruiz and Berlanga, 2002; Conchedda et al., 2008; Selvam et al., 2003; Chen et al., 2013), and the applications of the supervised classification approaches were the most effective and robust method for classifying mangrove based on traditional satellite remote sensing data. For the reason, the research was adopted to detect spatial and temporal change in mangrove during the past decades by using Landsat satellite data with a supervised classification approach. Hence, the results provided important information for the local government to make a decision for better land use planning and land management in the future. One more important reasonable that the MODIS data and Landsat are available for free download.

1.3. Research objectives

The dissertation was mainly divided into two parts: using MODIS data to monitor rice crop area and using Landsat imagery to detect changes in mangrove forests during the past decades. Therefore, our goal was:

i) To contribute to development of a low-resolution database for regional agriculture monitoring using MODIS data. The goal of the research was therefore to investigate the applicability of MODIS data for monitoring rice cropping systems in the study area using time-series MODIS NDVI data;

ii) To map the mangrove forests in the Mekong Delta by using Landsat imagery in the past three decades from 1989 to 2015. The specific objectives were followed:

- To produce the multi-temporal mangrove maps for 1989, 1998 and 2015, and
- To detect and analyze the changes in mangrove in the periods 1989-1998, 1998-2015, and 1989-2015; and
iii) To determine evapotranspiration in the Mekong Delta from 2000 to 2015 using multi-satellite data as well as to identify changes of water resources in the same period.

1.4. Literature review

This chapter reviews existing theories and results of previous studies that are related to the research objectives. Crop classification using time-series low-resolution satellite data and mangrove forests interpretation by using optical remote sensing were particularly reviewed. The chapter also highlights research gaps and potential contributions of this research.

1.4.1. Moderate resolution imaging spectroradiometer (MODIS)

MODIS is a key instrument aboard Terra (EOS AM) and Aqua (EOS PM) satellites. Terra's orbit around the earth is timed so that it passes from North to South across the equator in the morning, while Aqua satellite passes South to North over the equator in the afternoon. Terra MODIS and Aqua MODIS are viewing the entire earth's surface every 1 to 2 days, acquiring data in 36 spectral bands. MODIS has a viewing swath width of 2,330 km, its detectors measure between 0.405 and 14.385 μm, and it acquires data at three spatial resolutions of 250 m, 500 m, and 1,000 m.

The MODIS data greatly improve the understanding of global dynamics and processes occurring on the land, in the oceans, and in the lower atmosphere. It is playing a vital role in the development of validated, global, interactive earth system models able to predict global change accurately enough to assist policy makers in making sound decisions concerning the protection of the environment. There are 44 standard MODIS data products that scientists are using to study global change. These
products are used by scientists from a variety of disciplines, including oceanography, biology, and atmospheric science. In this section, MODIS Surface Reflectance Product MOD09 was used for rice crop classification.

1.4.1.1. The MODIS surface reflectance product MOD09

The MODIS MOD09 is computed from the MODIS Level 1B land bands 1, 2, 3, 4, 5, 6, and 7 (at 648 nm, 858 nm, 470 nm, 555 nm, 1,240 nm, 1,640 nm, and 2,130 nm, respectively).

**Table 1.1.** Description of the seven land bands of MODIS and their primary use.

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength (nm)</th>
<th>Description</th>
<th>Resolution</th>
<th>Primary use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>620 - 670</td>
<td>Red</td>
<td>250 m</td>
<td>Land cover transformation, vegetation chlorophyll</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Cloud amount,</td>
</tr>
<tr>
<td>2</td>
<td>841 - 876</td>
<td>Near-infrared</td>
<td>250 m</td>
<td>vegetation land cover transformation</td>
</tr>
<tr>
<td>3</td>
<td>459 - 479</td>
<td>Blue</td>
<td>500 m</td>
<td>Soil/vegetation differences</td>
</tr>
<tr>
<td>4</td>
<td>545 - 565</td>
<td>Green</td>
<td>500 m</td>
<td>Green vegetation</td>
</tr>
<tr>
<td>5</td>
<td>1,230 - 1,250</td>
<td>Short wave infrared</td>
<td>500 m</td>
<td>Leaf/canopy differences</td>
</tr>
<tr>
<td>6</td>
<td>1,628 - 1,652</td>
<td>Short wave infrared</td>
<td>500 m</td>
<td>Snow/cloud differences</td>
</tr>
<tr>
<td>7</td>
<td>2,105 - 2,155</td>
<td>Short wave infrared</td>
<td>500 m</td>
<td>Cloud properties, land properties</td>
</tr>
</tbody>
</table>
Each MODIS Level-1B data product contains the radio-metrically corrected, fully calibrated and geo-located radiances at aperture for all 36 MODIS spectral bands at 1,000 m resolution. The product is an estimate of the surface spectral reflectance for each band as it would have been measured at ground level if there were no atmospheric scattering or absorption. The spatial resolutions of MOD09 product are 250 m (bands 1 and 2) and 500 m (bands 1 to 7). The data are broken into granules approximately 5 min long and stored in hierarchical data format (.hdf). Table 1.1 gives the characteristics of the MODIS bands dedicated to land.

1.4.1.2. Overview of MODIS data preprocessing

This section briefly reviews the pre-processing of MODIS data including: calibration, atmospheric correction, and radiometric correction.

a. Data calibration

Data calibration is a process of converting DN into at-satellite radiances. There are three types of calibrations associated with MODIS: L1B emissive calibration, L1B reflective calibration, and spectral calibration. Two external calibration techniques that MODIS uses for data calibration are views of the moon and deep space. Looking at the moon provides a second method for tracking degradation of the Solar Diffuser, and looking at deep space provides a photon input signal of zero, which is used as an additional point of reference for calibration (NASA, 2011b).

b. Atmospheric correction

Atmospheric correction is a process of removing effects of the atmosphere on the reflectance values of images taken by satellite sensors. This correction is an important
process that significantly improves the accuracy of image classification. The atmospheric correction algorithm (i.e., Atmospheric Correction Algorithm: Spectral Reflectance MOD09) applied to MODIS land bands 1 to 7 uses aerosol and water vapor information that are derived from MODIS itself. It also takes into account the directional properties of the observed surface. The MODIS data used in this study has thus been atmospherically corrected to account for the effects of atmospheric gases, aerosols, and thin cirrus clouds (Vermote and Vermeulen, 1999).

c. Radiometric correction

Radiometric correction is used to modify DN values to account for noises. This is done because the radiance measured by the satellite sensor over a given object is influenced by factors, such as aerosols, changes in scene illumination, atmospheric conditions, viewing geometry, and instrument response characteristics. The MODIS data used in this study are radio-metrically corrected, fully calibrated and geo-located radiances at-aperture for all spectral bands and are processed to Level 3G. The spectral range is from 0.45 to 2.15 μm (Zhang et al., 2003; Wardlow et al., 2007; NASA, 2011a).

1.4.2. Summary of methods for noise filtering

The MODIS NDVI vegetation indexes have been appreciated for vegetation dynamics studies and crop monitoring (Son et al., 2013; Chen et al., 2011; Mkhabela et al., 2011; Ren et al., 2008), and demonstrate a good range and sensitive for monitoring and assessing spatial and temporal variations in vegetation amount and conditions. Theoretically, the vegetation time-series data profiles should be
continuous and smooth curves. However, there were some noises still presented on MODIS NDVI time-series data due to cloud contamination, complexities of atmospheric correction processes and individual band noise that have not been eliminated well yet. Therefore, it is necessary to perform the noise filtering method to reduce noises from time-series data for further analysis and construct the high quality time-series vegetation indexes.

For this problem, several methods were performed based on interpolation of time-series data which has been proposed to filter out such noises. Generally, they can be categorized into two types. The first methods that remove noise in the time domain like the Best Index Slope Extraction (BISE) method, the Gaussian fitting functions (Atkinson et al., 2012), the weighted least-square linear approach, and the Savitsky-Golay filter. The second types of filtering methods includes noise-removal in frequency domain such as Fourier analysis (Roerink et al., 2000; Canisius et al., 2007), and wavelet transformation (Chen et al., 2011; Sakamoto et al., 2006).

In comparison among above-mentioned filtering methods, the BISE has been used for vegetation and forest type classification (Xiao et al., 2002), but its effectiveness depends on the researcher’s experience, hence, it is difficult to determine the optimal window for smoothing as well as to produce consistent and reasonable results. The Gaussian fitting were used to extract vegetation seasonality information (Jonsson and Eklundh, 2002) and it can work well with favorable conditions but it requires users to determine a set of the maxima and minima to which the local function can be fitted. Moreover, it is difficult to identify these two parameters from the noise presented on time-series data. The result was proposed by Fourier transform often shows large
biases compared to original time-series data and often generates physically meaningless harmonics when the degree of non-linearity in a time-series increases (Huang et al., 1999) and this problem can be overcome by wavelet transform (Chen et al., 2012). Besides that, the Savitsky-Golay filter approach which uses a simplified least-square-fit convolution for smoothing and computing the derivatives of a set of consecutive values (a spectrum), but it also requires empirical analyses to determine the width of the smoothing window and the degree of the smoothing polynomial.

The Fourier filter remains some demerits, such as the degree of nonlinearity in time series increases, and the decomposition often generates large sets of physically meaningless harmonics, while in wavelet transform it is required to determine a proper mother wavelet prior to the decomposition. In comparing the performance of Fourier and wavelet transforms as filtering methods for studying seasonal NDVI responses from rice fields in Japan, Sakamoto et al. (2005) concluded that wavelet transform (using three types of mother wavelets: Coiflet 4, Symlet 6 and Debeutries 13) gave remarkably better results than Fourier transform. Some previous studies reported that the Empirical Mode Decomposition (EMD) is a powerful method for noise removal and analyzing data from nonlinear and non-stationary processes based on an adaptive basis, but it is time-consuming and complexity in process.

In this study, the wavelet transform was used to filter out noises from the time-series NDVI which has been proved as a suitable filter for noise removal of time-series data (Chen et al., 2011). The wavelet transform can analyze signals in time-frequency space. Its strength is the feasibility of identifying and reducing noises while maintaining useful information in time-series data. This method has been developed
as a powerful tool in signal processing and successfully used for noise removal. From
the NDVI time-series data affected by clouds and atmospheric conditions, it is
difficult to discriminate a rice cropping system and identify the heading date of each
crop. The wavelet transform was applied to remove high frequency that related to
noises on time-series data and the noise is significantly mitigated on the time-series
MODIS NDVI data after filtering. The smoothed time-series profiles of NDVI can
show the temporal pattern characteristics of rice cropping system throughout the year
(Chen et al., 2011) and the characteristic points including the maximum point and
inflection point can be identified. It is possible to detect the phenological stages of
rice such as the timing of planting, heading and harvesting (Sakamoto et al., 2006).

1.4.3. Landsat data

Landsat satellite data have been produced, archived, and distributed by the United
States Geological Survey (USGS) since 1972. Users rely on these data for historical
study of land surface change, but shoulder the burden of post-production processing
to create applications-ready data sets. In compliance with guidelines established
through the Global Climate Observing System, USGS has embarked on production
of higher-level Landsat data products to support land surface change studies. Landsat
satellite imageries used for this research were collected from the USGS via the
website www.earthexplorer.usgs.gov. The Earth Explorer website provides free
satellite data to users. Three periods: 1989, 1998, and 2015 were used for this research
in all site studies (Table 1.2).
Table 1.2. Landsat imagery data collected from the USGS

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Year</th>
<th>Band</th>
<th>Spatial resolution (m)</th>
<th>Temporal resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat TM</td>
<td>1988/1989</td>
<td>7</td>
<td>Multi: 30</td>
<td>16 days</td>
</tr>
<tr>
<td>Landsat ETM+</td>
<td>2001</td>
<td>8</td>
<td>Multi: 30</td>
<td>16 days</td>
</tr>
<tr>
<td>Landsat 8 OLI</td>
<td>2014</td>
<td>11</td>
<td>Multi: 30</td>
<td>16 days</td>
</tr>
</tbody>
</table>

In one hand, the image acquisition dates are very important because vegetation and crops reflect differently at the beginning and the end of the rainy season due to phenological and temperature disparities, and their reflectance varies from a dry season to a rainy season. That is the reason why all the data acquired at the same season and the same sensor to perform image classification and change detection. In the other hand, the images quality were categorized by visual evaluation as no could in all the study sites. That means, this study ignored effected by cloud and shadow, hence cloud shadow removal was not necessary.

The Landsat image used has a 30-m spatial resolution, 16-days temporal resolution and corrected at level 1T (the Standard Terrain Correction). The level 1T provides systematic radiometric and geometric accuracy by incorporating the ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy. Geodetic accuracy of the product depends on the accuracy of the ground control points and the resolution of the DEM used. The Landsat images were projected to World Geodetic System 1984 (WGS84) Universal Transverse Mercator (UTM).
Table 1.3. Band line up, wavelength, and description of each Landsat band

<table>
<thead>
<tr>
<th>Band name</th>
<th>Landsat TM/ETM+</th>
<th>Landsat 8 OLI</th>
<th>Useful for mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wavelength (µm)</td>
<td>Wavelength (µm)</td>
<td></td>
</tr>
<tr>
<td>Coastal</td>
<td>-</td>
<td>0.43 – 0.45</td>
<td>Coastal and aerosol studies</td>
</tr>
<tr>
<td>Blue</td>
<td>0.45 - 0.52</td>
<td>0.45 – 0.51</td>
<td>Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation</td>
</tr>
<tr>
<td>Green</td>
<td>0.52 - 0.60</td>
<td>0.53 – 0.59</td>
<td>Emphasizes peak vegetation which is useful for assessing plant vigor</td>
</tr>
<tr>
<td>Red</td>
<td>0.63 - 0.69</td>
<td>0.64 – 0.67</td>
<td>Discriminates vegetation slopes</td>
</tr>
<tr>
<td>NIR</td>
<td>0.76 - 0.90</td>
<td>0.85 – 0.88</td>
<td>Emphasizes biomass content and shorelines</td>
</tr>
<tr>
<td>SWIR 1</td>
<td>1.55 - 1.75</td>
<td>1.57 – 1.65</td>
<td>Discriminates moisture content of soil and vegetation; penetrates thin clouds</td>
</tr>
<tr>
<td>SWIR 2</td>
<td>2.08 - 2.35</td>
<td>2.11 – 2.29</td>
<td>Improved moisture content of soil and vegetation and thin cloud penetration</td>
</tr>
<tr>
<td>Pan</td>
<td>0.52 - 0.90</td>
<td>0.50 – 0.68</td>
<td>15 meter resolution, sharper image definition</td>
</tr>
<tr>
<td>Cirrus</td>
<td>-</td>
<td>1.36 – 1.38</td>
<td>Improved detection of cirrus cloud contamination</td>
</tr>
<tr>
<td>TIRS 1</td>
<td>10.4 - 12.50</td>
<td>10.6 – 11.19</td>
<td>100 meter resolution, thermal mapping and estimated soil moisture</td>
</tr>
<tr>
<td>TIRS 2</td>
<td>-</td>
<td>11.5 – 12.51</td>
<td>100 meter resolution, thermal mapping and estimated soil moisture</td>
</tr>
</tbody>
</table>
The sensors on board the Landsat Satellites record the surface reflectance of electromagnetic (EM) radiation from the sun in several discreet bands. EM radiation refers loosely to light waves and other energy such as x-rays or microwaves. Essentially, the satellite 'sees' reflected sunlight in portions of the spectrum including visible light and three bands beyond visible light (within the infrared portion of the spectrum).

This is the reason why band combinations yield different results depending on what land cover type is identified and what specific changes need to be identified. These bands can be seen in Table 1.3 and showing how the new bands from Landsat 8 line up with Landsat 5 and 7 and a brief description of the assigned color that is associated with the spectral response.

The level of detail (spatial resolution) is often the most interesting aspect of viewing satellite image, but less appreciated is how changes in irradiative energy reflected by different surface materials are used to identify features of interest.

1.4.4. Image classification using hard classification technique

One of the main objectives of this study is to investigate the applicability of time-series MODIS NDVI 250 m data for mapping rice cropping systems and Landsat imagery for mapping mangrove forests in the study area. Data were processed by supervised classification approach (Support Vector Machines).

As a pixel produced by Landsat and MOD09Q1 product covers approximately 0.9 ha and 6.25 ha on the ground, respectively, the fields in the study area (including rice and mangrove) ranged from less than one to several hectares in size. Obviously, a
MODIS and Landsat pixel is typically larger than a field and possibly contains more than one land-use class on the ground. The problem of mixed pixels cannot be solved simply by increasing the spatial resolution (Campbell, 2002).

Over the past couple of years the Support Vector Machines have been demonstrated a great potential for classification of high dimensional satellite data (Gualtieri and Cromp, 1998; Huang et al., 2002; Foody and Mathur, 2004a; Foody and Mathur, 2004b). In this section, endeavors are made to review the theoretical base and utilization of the mapping algorithm for crop and forest mapping using time-series remotely-sensed data as well as Landsat imagery.

**Support vector machines**

The hard classification techniques, such as the Maximum Likelihood Classification Classifier (MLC), neural network, and decision tree, classify the image on a pixel-basis into different categories or land cover classes. Since 1970s, shortly after the first Landsat satellite launched, numerous classification algorithms have been developed for land use/land cover classification (Townshend, 1992; Hall et al., 1995).

Among these classifiers, the MLC has been the most commonly applied classification technique due to its well-developed theoretical base and its successful application with different data types and classification schemes (Bolstead and Lillesand, 1991). The MLC is a parametric classification algorithm that assumes a class signature in normal distribution (Gaussian statistical distribution) and statistically calculates the probability that a given pixel belongs to a specific class (Jensen, 1996). Each pixel is assigned to the class that has the highest probability (Richards and Jia, 1999).
The Support Vector Machine algorithm (Boser et al., 1992; Cortes and Vapnik, 1995) is a non-parametric hard classifier (Foody and Mathur, 2004a). It is based on a statistical learning theory. The Support Vector Machines use a kernel function to non-linearly project the training data in the input space into a high dimensional space where the classes are linearly separable. The Support Vector Machines have been successfully applied in remote sensing for classification of land use/land cover types (Otukei and Blaschke, 2010).

This algorithm has been demonstrated to give better classification results among the maximum likelihood, univariate decision trees and back propagation neural networks (Huang, 2002). However, it is also claimed that using the Support Vector Machines for classifying high-dimensional data sets can produce more accurate results compared with traditional classifiers, but the outcome depends on the use of kernels, the choice of parameters for a chosen kernel and the method used to generate the Support Vector Machines (Huang et al., 2002).

Kernel functions that are commonly used in the Support Vector Machines can be categorized into four groups. They are linear, polynomial, Radial Basis Function (RBF) and sigmoid kernels. The RBF and polynomial kernels are the two commonly-used ones in remote sensing for classification of satellite images (Huang et al., 2002; Keerthi and Lin, 2003; Pal and Mather, 2005). It is found that using the RBF kernel for classification of hyperspectral image the best results were achieved (Camps-Valls, 2005).

The RBF is a non-linear kernel that maps samples into a higher dimensional space so that it can handle the case when the relationship between class labels and attributes is
nonlinear. This kernel also has less numerical computational difficulties (Hsu et al., 2010). The Support Vector Machines use training data to perform the classification. The Support Vector Machines seek pure pixels automatically.

1.5. Thesis outline

The structure of this dissertation is organized into four chapters as follows:

1. Introduction presents a general background of this research. The contents of this chapter consists of an overview of the study, statement of the problem, research objectives, and literature review. In details, literature review reviews the existing studies and reports that are relevant to the research objectives. This chapter also highlights research gaps of these existing studies so as to gain the firm understanding of the theoretical base of methods and empirical studies of crop and mangrove forests classification.

2. Methodology provides algorithms that were used in the study for mapping rice cropping systems using MODIS data as well as mangrove forests using Landsat imagery. This chapter includes study area and data collection.

   • Study area describes the study area profile, which comprises of descriptions of rice cropping systems, hydro-meteorological, distribution of mangroves, threatened, and the mangrove characteristics, and rationale for selecting the study area.

   • Data acquisition and preparation are presented in this chapter.

3. Results and discussion are divided into three cases:

   • Rice crop mapping deals with the classification of rice cropping systems in the
study area. It also presents the results obtained from a case study wavelet analysis for noise filtering of the time-series MODIS NDVI data. The results of rice crop classification using the Support Vector Machines and the results of classification accuracy assessment are presented.

- Mangrove forest mapping results with the Support Vector Machines approach are shown in this chapter. A long time changes in mangrove forest was also analyzed and discussed.

- Long-term water balance in the Mekong Delta was discussed and analyzed from the land cover mapping results above.

4. General discussion and conclusions address general discussion of the research findings of this study. It also draws conclusions based on the results. Possibilities for further studies are finally recommended based on the research findings and conclusions.
2. METHOD

2.1. Study area

2.1.1. Location and topography

The study area is located in the southern Vietnam, between latitude 8.5-11.0° and longitude 104.5-106.64° (Figure 2.1). It covers an area of approximately 40,000 km². There are 13 provinces in the study area, including Long An, Tien Giang, Ben Tre, Vinh Long, Tra Vinh, An Giang, Dong Thap, Kien Giang, Can Tho, Hau Giang, Soc Trang, Bac Lieu, and Ca Mau.

Figure 2.1. Map of the study area relative to national geography.

The study area geography is mostly plateaus, except for some mountainous and hilly areas that can be observed in Kien Giang and An Giang provinces. The average altitude of the delta is about two meters above the mean sea level. The lowest area is observed in Dong Thap province with an altitude of 0.5 m below the mean sea level.
The land can be divided into two ecological types, inland areas and coastal areas. Inland areas are covered with a dense irrigation network and benefit from a fertile soil formed by sediment during flood seasons which allow practicing double or triple-cropping of rice. Coastal areas are prone to salt intrusion in the dry season which limits the soil fertility; therefore the major cropping patterns are single rice with shrimp farming.

2.1.2. Hydro-meteorological characteristics

The study area has a tropical monsoon climate with the annual mean temperature of 27.5°C. During the coolest months (December and January), the mean temperature is from 23 to 25°C and during the warmest months (March and April) it is more than 33°C. There are two distinct seasons with an annual average rainfall of 1,442 mm. In the western part, rainfall mounts up to 2,000 - 2,500 mm; in the central part, it is 1,200 - 1,500 mm; and towards the eastern part, it is 1500 - 1600 mm. The wet season occurs from May to November bringing approximately 80% of the total rainfall. The dry season runs from December to April with about 10% of the total annual rainfall amount.

The more frequent rainfall deficiencies that have happened in recent years have triggered soil moisture deficits as well as salt-water intrusion, and negatively affected rice crops in the region. Salt-water intrusion is expected to become more seriously as a result of increasing diversions of water for dry season irrigation (White et al., 1996). The decrease of water flow of the Mekong River during the dry season is further exacerbated by the construction of hydroelectric power plants by upstream countries.
(MRC, 2002), and possibly by the effects of global warming which is forecasted to induce increase of the water sea level in Southeast Asia by 2 mm/year (Tuong, 2001). The amount of water in the Mekong and Bassac rivers in the dry season was reduced drastically from estimated 2,500 m$^3$/s 30 years ago, to approximately 1,600 m$^3$/s in 2006 (MONRE, 2009). Consequently, the region was faced with drought. The Mekong River spreads over 4,200 km length from the Plateau of Tibet in China through Myanmar, Laos, Thailand, Cambodia, and Vietnam. From the Tonle Sap Lake of Cambodia, the river branches into the Mekong and Bassac Rivers before crossing Vietnam territory for a distance of 200 km and reaching the Eastern Sea. In the downstream of the Vietnamese Mekong Delta, the Mekong River branches into five tributaries, and the Bassac River branches into four tributaries.

The Vietnamese Mekong Delta has a complex network of natural streams and dense man-made canals. No fewer than 10,000 km of irrigation canals deliver water throughout the region. In the upstream of the delta, the region is influenced by rivers, while downstream of the region by the diurnal tidal movement of the Eastern Sea and the semi-diurnal tidal movement of the Western Sea.

The annual rainfall combined with the high level of water amount in the Mekong River results in regular floods of 0.3 to 3 m during the wet season, mainly from August to November with the highest flood in September. The entire area is dry during the dry season (December to April). When the river flow is reduced, salt-water intrudes the inland, especially during the dry season, affecting approximately 2100 km$^2$ of agricultural land in the coastal area (VMWR, 1994).
2.1.3. Rice production in the Mekong Delta

The Mekong Delta is not only a major rice-growing region in Vietnam but also in Southeast Asia. The cultivated area amounts up to approximately 27900 km² (or 71.6% of the total area of Mekong Delta). More than 90% of this agricultural land is allocated to rice production (Sub-NIAPP, 2000). Irrigated rice production is commonly practiced in the region, which is considered as a key source of income for more than 17 million inhabitants.

![Rainfall graph](image)

**Figure 2.2.** Rice cropping calendar in the Mekong Delta with reference to the monthly rainfall in 2008 at the Chau Doc rain-gauge station (Chen et al., 2011).

Rice production in the study area is based upon the availability of irrigation and suitable local climatic conditions. A year can be divided into five crop seasons: rainy season which starts from July/August and lasts until December/January; winter-spring from November/December to February/March; spring-summer from
March/April to May/June; summer-autumn from April/May to July/August; and autumn winter from July/September to October/December (Figure 2.2).

The rice cropping systems in this region are single crop rain-fed rice, double crop irrigated rice, double crop rain-fed rice, triple crop irrigated rice (I), and triple crop irrigated rice (II) (Table 2.1). The irrigated rice cropping uses short-term rice varieties (90 - 110 days). The single rain-fed rice cropping using long-duration varieties (160 - 180 days) is invariably practiced in areas where soils and irrigation were major constraints for short-term rice cultivation.

**Table 2.1. Rice cropping systems in the study area.**

<table>
<thead>
<tr>
<th>Rice cropping systems</th>
<th>Rice seasons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single crop rain-fed rice</td>
<td>Rainy season</td>
</tr>
<tr>
<td>Double crop irrigated rice</td>
<td>Winter-spring - summer-autumn</td>
</tr>
<tr>
<td>Double crop rain-fed rice</td>
<td>Summer-autumn - autumn-winter</td>
</tr>
<tr>
<td>Triple crop irrigated rice (I)</td>
<td>Winter-spring - summer-autumn - autumn-winter</td>
</tr>
<tr>
<td>Triple crop irrigated rice (II)</td>
<td>Winter-spring - spring-summer - summer-autumn</td>
</tr>
</tbody>
</table>

Double and triple irrigated-rice cropping systems are practiced in areas that receive irrigation water. In triple irrigated rice cropping systems, depending on area where irrigation is under a favorable condition, an extra crop can be added. Double rain-fed rice cropping is often practiced along the coastal areas under predominantly rain-fed conditions, where irrigation was major constraints for short-term rice cultivation.
2.1.4. Description of rice growth stages

The temporal aspect of rice growth is important for understanding of the NDVI responses of rice fields at different growing stages. Short-term rice varieties in the study area are from 90-110 days (Minh and Kawaguchi, 2002). There are three main phenological periods of a rice crop including sowing period, growing period (vegetative, reproductive and ripening stages), and fallow period (Le-Toan et al., 2003).

Figure 2.3. Rice growing stages (IRRI, 2007)

- Sowing period: the rice grains are sown at a high density, directly in flooded soil under 2 - 5 cm of water;
- Growing period: the change of rice growth from the vegetative stage to the reproductive stage on reaching the heading date. This period is characterized by an increase of the plant height, the number of tillers, and development of leaves. After heading, the growth height and biomass stops and the leaves begin to wither and die. The ripening stage is characterized by a decrease of leaf and stem moisture content and a decrease of the number of leaves. The
duration of the vegetative stage is approximately 60 days, reproductive stage (30 days), and ripening stage (30 days) (Yoshida, 1981; Sakamoto et al., 2005); and

- Fallow period: after harvesting, rice fields can be either bare or dry at the end of the dry season or covered with weeds in wet conditions.

2.1.5. Status and spatial distribution of mangrove forests in the Mekong Delta

Tropical mangrove forest ecosystems play an important role in coastal zones, not only in the biogeochemical cycle but also in the economic life of the region through activities such as aquaculture and fishing. Mangrove forests in the Mekong Delta used to cover more than 2500 km² (Hong and San, 1993). War, forest fire, collection of fuel wood and other human activities have resulted in reduction of the mangrove forests in the Mekong Delta. Especially, since the end of the 1990's, mangrove forests had been cleared for shrimp farming in many areas (Hong and San, 1993, Hong, 1995 and Hao, 1999).

Despite the many factors that had affected the mangroves of the Mekong Delta, the most important factor that contributed to mangrove destruction was the shrimp culture activities. The herbicides sprayed by the USA in the war (1962–1971) destroyed about 1049 km², about 36% of the total mangrove area in South Vietnam (NAS, 1974). Population pressure led to an increased need for land for agricultural production. In addition, environmental degradation and sedimentation have also negatively affected mangrove forests (Macintosh, 1996 and Le and Munekage, 2004).

Within the coastal area shrimp culture is the major aquaculture practice. The rearing of shrimps in the Mekong Delta increased by 3500% between 1976 and 1992.
Between 1980 and 1987 shrimp culture has increased from 30 km$^2$ to 40 km$^2$. During this period shrimp farming was based on natural seed supply, no supplementary feeding, and the average production was 250 kg/ha/year. From 1988 to 1992 shrimp culture has increased to 600 km$^2$. Gradually hatchery produced post larvae and supplementary feeding with trash fish were introduced. The production gradually increased to 450 kg/ha/year.

By 2012, Ca Mau Province had about 690 km$^2$ of mangroves accounting for about 49.6% of the whole country (1390 km$^2$) (MARD, 2013; Ca Mau Portal, 2014). Natural and anthropogenic factors in the mangroves around Ca Mau peninsula have caused erosion along the East sea coast and accretion along the Gulf of Thailand shoreline. As stated by the Man and Biosphere program Vietnam (2008), these changes led to the loss of huge stretches of mangroves along East Sea resulting in the decrease and, in some cases, loss of mangrove environmental and ecosystem services. The effects included loss of spawning grounds for aquatic species and the loss of the wave buffering and sheltering effect of mangroves, threatening residential areas and infrastructure behind the mangrove (Man and Biosphere program Vietnam, 2008).

In addition, by the end of the 21st century, the average sea level in the study area is projected to rise 59-75 cm and 62-82 cm along the East Sea and the Gulf of Thailand, respectively (MONRE, 2012). However, the change in the mangrove shoreline due to accretion and erosion at Ca Mau peninsula had not been quantified but merely observed. Key weaknesses in previous attempts at government mangrove rehabilitation had been uniform application of homogeneous monoculture plantations with little consideration for maintenance needs or coastal dynamics, which dictate
suitability of mangrove rehabilitation at any given sites (IUCN, 2012). It is, therefore, very important to detect quantitatively the changes of mangrove shoreline. This will be used effectively to predict the changes of coastal ecosystem boundaries and enable advanced planning for specific sections of coastline, to minimize or neutralize losses, to inform provincial rehabilitation efforts and reduce threats to coastal development and human safety (Dahdouh-Guebas, 2002; Gilman et al., 2007; IUCN, 2012).

2.2. Data acquisition and pre-processing

2.2.1. MODIS data

The eight-day MODIS products were used in this study for classification of rice cropping systems in the region (MOD09Q1: 250-m resolution). The data of the product was collected from the National Aeronautics and Space Administration (NASA) through their website: http://reverb.echo.nasa.gov/. The MOD09Q1 data was used for classification of rice cropping systems from 2002, 2005, 2010, and 2015. This data product has two spectral bands: red and near infrared.

The NDVI was used for rice crop classification because this index is strongly correlated with the amount of green vegetation. To create the time-series NDVI dataset for each year, the NDVI for every eight-day MODIS scene was first calculated. There were a total of 46 NDVI scenes each year, and they were then stacked into one eight-day composite scene with 46 bands.

2.2.2. Landsat data

A series of Landsat imageries in 1989, 1998, and 2015 were collected from the USGS via the website, http://earthexplorer.usgs.gov/. Images acquisition dates are very
important because vegetation and crops reflect differently at the beginning and the end of the rainy season due to phenological and temperatures disparities, and their reflectance varies from the dry season to the rainy season. Therefore, satellite data were collected in the same dry season during three periods. The Landsat TM and ETM+ have 7 spectral bands with a spatial resolution of 30 m for bands 1-5 and 7. The TM and ETM+ band 6 (thermal infrared) is acquired at 120 m and 60 m but are resampled to 30 m pixels, respectively. The Landsat 8 data have 9 spectral bands with a spatial resolution of 30 m for bands 1-7 and 9, while band 8 has a spatial resolution of 15 m (panchromatic band).
Figure 2.4. NDVI MODIS 250 m image acquired on 25 January 2015 (DOY 025).

The level 1T provides systematic radiometric and geometric accuracy by incorporating ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy and were projected to World Geodetic System 1984 (WGS84) Universal Transverse Mercator (UTM).
2.2.3. Ancillary data

The land-use map of the Mekong Delta in 2014 (scale: 1/250,000 in Figure 2.6) provided by Department of Land Resources, Can Tho University, Vietnam was used as the ground reference for the investigation of rice fields as well as the distribution of mangrove forests. The map was constructed from various data including Landsat ETM Plus acquired in 2014 and provincial land-use maps (scale: 1/50,000) produced by the Department of Agriculture and Rural Development of provinces and the Department of Natural Resources and Environment. The original resolution of the land-use map was 30 m.
2.2.4. Generating a ground truth image for accuracy assessment

The ground truth image was created after the field investigation. The sizes of rice fields in the study area generally ranged from one to several hectares. To ensure that the ground truth image did not contain mixed pixels, a 250 m resolution grid was created for the 2014 rice crop map and then the percentage of crop coverage was calculated each cell. Only cells with more than 90% crop cover were considered for creating the ground truth image. This step was done for validation rice crop map only.

Based on the information collected from the field surveys and reference data sources including Landsat images (30 m resolution) gathered from the United States Geological Survey (USGS) through the website:
http://edcsns17.cr.usgs.gov/NewEarthExplorer, and provincial land-use maps in 2014 (scale: 1/50,000), we generated a vector map for sampling areas was generated using cells with more than 90% crop cover.

The map was then converted to a raster form and used for classification accuracy assessment. A number of 1500 ground truth pixels were randomly selected from this ground truth image using the Messene twister algorithm (Matsumoto and Nishimura, 1998) and used for accuracy assessment by comparing with the classification maps (Figure 2.7). In the same way, this research also extracted randomly pixels (500 points) for checking accuracy result with the classification result which interpreted from Landsat data (Figure 2.8).
Figure 2.7. Ground-truth pixels (500 pixels each class) randomly generated from the ground truth image were used for classification accuracy assessment.
Figure 2.8. Ground-truth pixels (100 pixels each class) randomly generated from the ground truth image were used for classification accuracy assessment.

2.2.5. Reason for selecting the study area

Rice is the major economic crop in the study area with approximately 20000 km$^2$ or 53% of the country rice-growing area. In recent years, rice crops in the region have adversely been affected from the lack of water for irrigation, deficient soil moisture and encroachment of saltwater during the dry season. This was caused by to the fact that the level of the Mekong River fell, the river levels in the study area dropped and seawater further encroached into inland rice fields.

The deficiency of surface soil moisture coupled with salinity intrusion has negatively damaged rice crops in the study area, especially during the dry season. Approximately 7000 km$^2$ of rice were affected by salinity, particularly during the dry season and
annually (Bui and Nguyen, 2004). On the other hand, demands for economic
development have caused drastic changes in rice cultivation practices and water and
land management in the study area. Many parts of the study area, especially in the
upper region, were now completely protected from annual flooding by systems of
high dykes. Farmers living inside the dyked areas were able to produce three crops
per year (Howie, 2005). Similarly, in the coastal region remarkable changes in rice
cultivation practices related to shrimp farming could also be found. An effective rice
monitoring program for the region is thus also important to provide land-use decision
makers with accurate information on rice growing areas so that they can plan better
economic development strategies as well as ensure security of the food supply for the
region and the country.

In the other side of the study, it is known that mangrove ecosystems serve as nursery
grounds for many marine shrimp and fish species (MacNae, 1974 and Mohamed and
Rao, 1977) and it has been demonstrated that 1 ha of mangrove forests support 100-
1000 kg/year of marine fish and shrimp catch (Hambrey, 1996; Lal, 1990;
Martosubroto and Naamin, 1977; Primavera, 1991; Ross, 1975; Staples et al., 1985
and Turner, 1977). This clearance of mangrove in the Mekong Delta certainly had an
impact on the marine fish production and catch.

The growth of shrimp culture in the Asian region had generally not been guided by
relevant national development plans nor had the industry been adequately managed
(Chua and Tech, 1990). Obviously, the growth of shrimp farming was still driven by
market forces, wherein profitability determined the rate of expansion. According to
Bailey (1988) “the expansion of shrimp culture in mangrove habitat generally
involves the transformation of a multi-use/multi user coastal resource into a privately owned single purpose resource. Moreover, the costs of coastal ecosystem disruption for society may include coastal erosion, saltwater intrusion into groundwater and agriculture fields, and a reduction in supply of a wide range of valuable goods and services produced from the resources available in mangrove forests or other coastal wetlands”. Coastal aquaculture development projects mostly consider only the positive returns and often under-estimate or even neglect the adverse consequences. Hambrey (1996) included environmental costs of shrimp culture in mangrove areas as the sum of the Net Present Values of the non-conversion uses. These include charcoal production, mud-crab fisheries, offshore fisheries and any other significant activities or functions. He concluded that the economic gain of semi-intensive (2-3 t/ha/year) and intensive shrimp culture (4-8 t/ha/year) still outweighs the negative impacts. However, production rates of shrimp culture in the Mekong Delta were (and still are far) below these production levels. Therefore the overall economic picture of shrimp culture development in the Mekong Delta could be a negative one.

2.3. Rice crop classification using Support Vector Machines

In this section, the classification of rice cropping systems using time-series MODIS NDVI 250 m data was performed. The Wavelet transform was first used for noise removal from the time-series NDVI data. The hard classification algorithms (Support Vector Machines) was then applied to the filtered data to test the crop classification performance of the method. Figure 2.9 illustrates a flowchart of the method used in this study for classification of rice cropping systems in the Mekong Delta.
The classification procedure comprises of four main steps: 1) the time-series NDVI data were filtered with the Wavelet transform, 2) temporal NDVI profiles of rice cropping systems which were extracted from the filtered time-series NDVI data were then analyzed to select training patterns, 3) the Support Vector Machines were applied to the filtered time-series data for classification of rice cropping systems using these training patterns, and 4) the classification results were finally assessed using the ground truth data.

**Figure 2.9.** Flowchart of the method used for classification of rice cropping systems.
2.3.1. Time-series NDVI construction

The MODIS data was formatted in Sinusoidal projection and then re-projected into the Universal Transverse Mercator coordinate system (zone 48N). The re-projected images were then mosaic and subset over the study area.

In order to construct time-series NDVI data, each 8 days MODIS NDVI image was first calculated. Totally, 46 images were generated for each years. Then, those images were stacked into one 8 days composite scene. The NDVI index was calculated using the following form,

\[
NDVI = \frac{NIR - Red}{NIR + Red}
\]  

(2.1)

where, NIR and Red are atmospherically or partially-atmospherically corrected surface reflectance of near infrared, and red bands, respectively. The range of the NDVI is from -1 to 1 and is the most often used for vegetation study and monitoring that reflect the vegetation greenness and indicates levels of healthiness in vegetation development.

2.3.2. Noise filtering of time-series NDVI data using Wavelet transforms

The wavelet transform is developed to analyze the properties of non-stationary signals (whose frequency response varies in time). The wavelet transform denoted as \( W(s, \tau) \) of a signal \( x(t) \) is defined as follows,

\[
W(s, \tau) = \frac{1}{\sqrt{s}} \int x(t)\Psi\left(\frac{t - \tau}{s}\right)dt
\]  

(2.2)
where x(t) is the analyzed input signal, Ψ(t) is a mother wavelet, s and τ are scaling and translation parameters (s > 0 and τ ∈ R). To obtain the Discrete Wavelet Transform (DWT), s and τ parameters need to be discretized. Discretizing by power of two (s = 2^j and τ = 2^k, where j and k are integers) will yield orthonormal basis functions for certain choices of Ψ. Thus, a discretely scaled and translated wavelet is presented as (2.3) and the DWT coefficients of x(t) can be obtained from (2.4).

\[
\Psi_{j,k}(t) = 2^{-j/2} \Psi(2^{-j}t - k), \quad (2.3)
\]

\[
W(j, k) = 2^{-j/2} \int x(t) \Psi(2^{-j}t - k) dt \quad (2.4)
\]

The multi-resolution analysis method (MRA) can be used to obtain the DWT of a discrete signal using the pyramid algorithm (Chen et al., 2011). The MRA decomposes a signal into different scales by iteratively applying a low-pass filter and a high-pass filter, and subsequently down sampling them by two. These filters retain the small and large scale components of the signals. At each level m of the pyramid, these detail (D_m) and approximation (A_m) components are computed according to (2.5) and (2.6), respectively.

\[
D_m(t) = \sum_k W_{m,k} \Psi_{m,k}(t), \quad (2.5)
\]

\[
A_m(t) = \sum_k V_{m,k} \Phi_{m,k}(t), \quad (2.6)
\]

where W_{m,k} is the wavelet coefficient and \Psi_{m,k}(t) is a scaling function. The original signal x(t) can be reconstructed from A_m and D_m using (2.7),
\[ x(t) = A_m(t) + \int_{j=1}^{m} D_j(t). \]  

(2.7)

In this study, Coiflet wavelet with order 4 was used in the wavelet transformation because it give the best result (among Daubechies and Symlet wavelet functions) for determining regional characteristics of rice phenology (Chen et al., 2011).

The most appropriate scales for the decomposition is given by the following equation is used.

\[ p = \frac{a\Delta t}{v_c}, \]  

(2.8)

where \( a \) is the scale, \( \Delta t \) is the sampling period, and \( v_c \) is the central frequency of the wavelet. The periodic signal period, \( p \), refers to the global temporal scale used in the wavelet decomposition. The central frequency of the Coiflets, \( v_c \), is 0.7272, and the sampling period of our time-series MODIS data, \( \Delta t \), is 8 days. For a \( 2^3 \), the approximation component for level 3, \( A_3 \), provides information about the seasonal variation over time scales of 88 days for a growing cycle of the rice crop.

2.3.3. Non-rice areas masking

The non-rice areas were masked out from satellite data using land use/land cover map (Figure 2.6). Because, the land use/land cover map still contains some errors. Moreover, the rice fields in Mekong Delta are generally small (about one to several ha) and fragmented by many canals and roads. Hence, the pixels extracted from the homogeneous rice area may contain some abnormal patterns caused by mixed-pixel problem. In order to remove those mixed-pixels, the 250 m resolution vector grid was
generated for the rice crop map and then calculated the percentage covers by rice crop for each pixel. The pixels with more than 90% covered by rice crop were used to mask out non-rice area and validation the classification results.

2.3.4. Selection of training patterns

The classification results obtained by the Support Vector Machines also greatly depend on the proper selection of training patterns. The training patterns used for the classification were randomly selected from the filtered time-series NDVI data based on the ground truth image. Training patterns trained in the Support Vector Machines and the ground truth pixels used for accuracy assessment were randomly selected from this ground truth image. In order to avoid possible bias due to the use of similar pixels for training and accuracy assessment, two groups of pixels from the ground truth image were selected: one for training and another for testing the classification accuracy.

2.3.5. Time-series NDVI classification (Support Vector Machines)

The Support Vector Machines was applied to classify rice cropping systems in the study area. A brief description of the Support Vector Machine algorithm is described in detail below.

Considering a simple case of two classes, given the training data with l number of samples represented by \( \{x_i, y_i\}, i = 1, \ldots, l \), where \( x \in \mathbb{R}^n \) is an n-dimensional vector, and an indicator vector \( y \in \{+1, -1\} \). The aim of the Support Vector Machines is to find an optimal separating hyperplane that can correctly separate the data into two classes. A hyperplane is defined as \( w \cdot x_i + b = 0 \), where \( x_i \) is the data point lying on
the hyper plane, parameter \( w \) determines the orientation of the hyper plane in space, and \( b \) is the bias that the distance of hyper plane from the origin. For the linearly separable case, a separating hyper plane can be defined for two classes as follows:

\[
\begin{align*}
w \cdot x_i + b & \geq +1 \text{ for all } y = +1 \text{ (class 1)} \quad (2.9) \\
 w \cdot x_i + b & \leq -1 \text{ for all } y = -1 \text{ (class 2)} \quad (2.10)
\end{align*}
\]

The training data points on these two hyper planes, which are parallel to the optimal separating hyper plane and represented as \( w \cdot x_i + b = \pm 1 \), are support vectors (Mathur and Foody, 2008). The two inequalities (2.9) and (2.10) can be combined into one inequality and is expressed in the following form,

\[
 y_i(w \cdot x_i + b) \geq 0 \quad (2.11)
\]

If a hyper plane exits that satisfies equation (2.11), the two classes are linearly separable. Thus, the classification decision function \( f(x) \) can be presented as,

\[
f(x) = \text{sign}(w^T x_i + b) \quad (2.12)
\]

The distance between two hyper planes \( (w \cdot x_i + b = \pm 1) \) is equal to \( \frac{2}{\|w\|} = 2\sqrt{w^T w} \).

The optimal separating hyper plane can be found by minimizing the term \( \frac{2}{\|w\|} \). Finally, the optimal separating hyper plane is required to solve the quadratic programming problem given by the following form,

\[
\begin{align*}
\min_{w, b} & \left[ \frac{1}{2} \|w\|^2 \right] \\
\text{subject to } & y_i(w^T x_i + b) \geq 1, i = 1, \ldots, l.
\end{align*}
\]

(2.13)
In the nonlinearly separable case, for example in classification of remotely-sensed data, it is impossible to classify the data into two classes by simply using a hyper plane that is defined by linear equations in the input space. The algorithm can be extended to allow for nonlinear decision surfaces (Cortes and Vapnik, 1995; Pal and Mather, 2004) to solve the optimization by introducing a $\xi$ slack variable as given in the following form,

$$
\min_{w, b, \xi} \frac{1}{2} w^T w + c \sum_{i=1}^{k} \xi_i
$$

Subject to $y_i (w^T \phi(x_i) + b) - 1 + \xi_i \geq 0, \xi_i \geq 0, i = 1, \ldots, 1$.

The training vectors $x_i$ are mapped into a higher dimensional space by the mapping function $\phi(x)$, and the Support Vector Machines find the optimal separating hyper plane with the maximal margin in this higher dimensional space. The penalty parameter $C$ allows striking a balance between the two competing criteria of margin maximization and error minimization.

The larger the $C$ value, the higher the penalty associated to misclassified sample (Melgani and Bruzzone, 2004). The slack variable $\xi_i$ indicates the distance of the incorrectly classified points from the optimal separating hyper plane (Oommen et al., 2008). Furthermore, the kernel function $K(x, x_i) = \phi(x)^T \phi(x_i)$ is introduced to make the computation easier in the feature space. Thus, the classification decision function can be expressed as follows:

$$
f(x) = \text{sign} \sum \alpha_i y_i K(x, x_i) + b
$$

(2.15)
where \( y_i(\alpha_i) \) is (i = 1, ..., l) are Lagrange multipliers and \( K(x,x_i) \) is the kernel function. Kernel functions commonly used in the Support Vector Machines can be categorized into four groups:

Linear kernel: \( K(x,x_i) = x^T x_i \)

Polynomial: \( K(x,x_i) = (\gamma x^T x_i + r)^d, \gamma > 0 \)

Radial basis function kernel (RBF): \( K(x,x_i) e^{-\gamma \|x-x_i\|^2}, \gamma > 0 \)

Sigmoid kernel: \( K(x,x_i) = \tanh(\gamma x^T x_i + r), \gamma > 0 \)

In the above-mentioned kernels, \( \gamma, r \) and d are kernel parameters. Among these kernels, the RBF and polynomial kernels are the most commonly used ones for classification of remotely-sensed data (Huang et al., 2002; Keerthi and Lin, 2003; Pal and Mather, 2005). In classification of hyperspectral imagery, the RBF kernel has been demonstrated to give the best classification results (Camps-Valls, 2005).

The chosen RBF kernel parameters, C and \( \gamma \) associated with the kernel affect the accuracy of the Support Vector Machines. The optimum parameter search thus needs to be done (Hsu et al., 2010) to find good parameters C and \( \gamma \) so that the Support Vector Machines can accurately classify the data. In this study, the parameters C and \( \gamma \) were determined by a grid search method using a cross validation approach. The idea underlying this method is that pairs of C and \( \gamma \) are tried and the one with the best cross-validation accuracy is taken. It is found that an exponentially growing sequence of C and \( \gamma \) can be utilized to identify good parameters (for example, \( C = 2^1, ..., 2^{15} \), and \( \gamma = 2^5, ..., 2^3 \)).
The grid search method can be performed using a coarse grid first. After identifying a better region on the grid, a finer grid search on that region can be carried out. Once the best C and γ are found, the whole training data is trained using these parameters for classification (Chen and Yu, 2007; Hsu et al., 2010).

2.3.6. Accuracy assessment

The post-classification refinement was employed to merge classes that have the same categories into rice cropping system classes. A 3x3 kernel-size majority filter was applied to the classification maps to reduce the salt-pepper effect of the classification map (Lillesand and Kiefer, 1999).

The classification result for the years 2015 were verified using the ground truth image and the other acillary data. The random check method has been intensively applied for classification accuracy assessment (Pal and Mather, 2004; Dewan and Yamaguchi, 2009). A pixels for each class were randomly generated from the ground truth image using the Mersenne twister algorithm (Matsumoto and Nishimura, 1998). The classification accuracy assessment was performed in such a way that these ground truth pixels were compared with that of the classification map using the confusion matrix. The Kappa coefficient and other parameters (producer and user accuracies) were utilized to measure the classification accuracy.

2.4. Mangrove forests mapping

This section presents the whole framework with data pre-processing, theory and approach in image processing, training samples, image classification, accuracy check,
and change detection and analysis. In addition, this chapter is also mentioned materials used in this research. All steps shown in the flowchart below.

**Figure 2.10.** General framework of the methodology on this research

### 2.4.1. Image pre-processing

This research used all spectral bands and NDVI (an additional band) to perform image classification. Because remotely sensed data acquired showed some forms of distortion or shift in geometric location from one sensor to the other. Therefore, image registration was necessary to fix this problem. Ground control points were used to correct geometric and a root mean square error (RMSE) of 0.58, 0.63, and 0.51 pixels in 1989, 1998, and 2015, respectively, were obtained in the study area. Landsat TM
and ETM+ used in Climate Data Records (CDR) products. The surface reflectance CDR generated from specialized software called Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS). The software applies MODIS atmospheric correction routines to Level-1 Landsat TM or ETM+ data. Water vapor, ozone, geopotential height, aerosol optical thickness, and digital elevation were input with Landsat data to the Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer models to generate the top of atmosphere (TOA) reflectance, surface reflectance, brightness temperature, and to mask clouds, cloud shadows, adjacent clouds, land, and water. In this case, the atmospheric correction only performed for Landsat 8 using Actor 2 (flat terrain, two geometric degrees-of-freedom (DOF)) software. The detailed parameters applied for the atmospheric correction presented in Table 2.2.

**Table 2.2.** Parameters used for atmospheric correction model.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Landsat 8 OLI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>2015/01/15</td>
</tr>
<tr>
<td>Date</td>
<td>2015/02/27</td>
</tr>
<tr>
<td>Solar zenith angle (deg)</td>
<td>35.5</td>
</tr>
<tr>
<td>Solar azimuth angle (deg)</td>
<td>123.3</td>
</tr>
<tr>
<td>Solar azimuth angle (deg)</td>
<td>135.3</td>
</tr>
<tr>
<td>Water vapor category</td>
<td>Tropical</td>
</tr>
<tr>
<td>Water vapor category</td>
<td>Tropical</td>
</tr>
<tr>
<td>Aerosol type</td>
<td>Maritime</td>
</tr>
<tr>
<td>Aerosol type</td>
<td>Maritime</td>
</tr>
<tr>
<td>Average visibility (km)</td>
<td>39</td>
</tr>
<tr>
<td>Average visibility (km)</td>
<td>39</td>
</tr>
</tbody>
</table>

As the results of images acquisition, the dates determined the image quality. Satellite data had different imageries on different dates in one period. Thus, reflectance normalization was performed with a histogram matching model and was developed within Imagine. It was identical to histogram matching based on equating cumulative
distribution functions. However, it used only image overlap areas to determine a lookup table for matching. This research was developed a model to match these images, called Histogram Matching Model (Figure 2.11). The goal was to generate satellite-image mosaics that are amenable to classification methods.

**Figure 2.11.** Histogram matching model was built by using ERDAS software.
Figure 2.12. Results a) before and b) after image normalization and cloud removal.
Furthermore, the site of study was a big size. Hence, the subset study area was reduced from the bulk, and the size of information was processed. This reduced the time consumed for the analysis of satellite images and also speeded up processing due to small amount of data processed. Besides, this area was covered by clouds during whole year. Hence, cloud removal was necessary to generate cloud free data for image classification.

The NSPI approach used a weighted linear model to predict spectral values of a target pixel from its neighboring similar pixels (Chen et al., 2011). Following idea of NSPI, neighboring pixels around cloudy pixels had a similar change trend of reflectance to cloudy pixels if their spectral characteristics were similar. Thus, it was possible to employ a modified NSPI approach to restore spectral values of cloudy pixels using the information of the neighboring similar pixels. For more details, see Chen et al., 2011.

2.4.2. Image classification

2.4.2.1. Selection and evaluation training samples

From the training samples, examples of land cover types of interest was identified on the image. The image processing software system was used to develop a statistical characterization of the reflectance each class. The image was classified by examining the reflectance each pixel and made a decision for which of the signatures it resembled the most (Eastman, 1995). For each study period, the Region of Interest (ROI) tool that provided in ENVI was used to select the training samples. Totally, there were eleven ROIs selected, including mangrove, mix shrimp and mangrove,
shrimp, cultivation, built-up, perennial plant, other plants, sediment, water, cloud, and shadows. Each ROI represented a land cover category. Then, it was evaluated.

A separability test is one of methods to determine how similar the distributions for two groups of pixels are. The Jefferies-Matusita (JM) distance was a function of separability that directly related to the probability of how good a resultant classification will be (Swain et al., 1971). As the results of training data selection, it was evaluated for agreement to classify the images by using the JM from the following form,

\[
BD = \frac{1}{8} \left[ \mu_i - \mu_j \right]^T \left( \frac{\varepsilon_i - \varepsilon_j}{2} \right)^{-1} \left[ \mu_i - \mu_j \right] + \frac{1}{2} \ln \left[ \frac{1}{\sqrt{\varepsilon_i + \varepsilon_j}} \right] 
\]

In which \( \beta_{ij} \) is the Bhattacharya Distance and is given by

\[
\beta_{ij} = \sqrt{2(1 - e^{-\beta_{ij}})} 
\]

where i and j are the two signatures classes, \( \mu_{i,j} \) is the mean vector signature for class i,j, \( \varepsilon_{i,j} \) is corresponding class covariance matrix signature, \( T \) is the transposition function. The JM distance had values 0 to 2. If JM value was greater than 1.9, then the classes show good separability. If the value was between 1.7 - 1.9, the separation between the classes was fairly good below 1.7, and the classes were poorly separated (Jensen, 1996).

**2.4.2.2. Landsat data interpretation**

The Support Vector Machine algorithm was a non-parametric classifier. The method based on statistical learning theory using a kernel function to non-linearly project the
training data in the input space into a higher dimensional space, where the classes were linearly separable. The Support Vector Machine has been widely applied in remote sensing for classification of land use or land cover types. It has been demonstrated to give better classification results among the maximum likelihood, univariate decision trees, and back-propagation neural networks (Huang et al., 2002). Nevertheless, it was also claimed that using the Support Vector Machine for classifying high-dimensional datasets can produce more accurate results comparing with the traditional classifiers, but the outcome greatly depends on the kernel types used, the choice of parameters for the chosen kernel and the method used to generate the Support Vector Machine.

However, because classified images often manifested a salt-and-pepper appearance due to the inherent spectral variability encountered by a classification when applied on a pixel-by-pixel basis. Therefore, it was desirable to “smooth” or “filter” the classified output. The median filtering in Convolution and Morphology tools in ENVI was used for post classification filtering by using a kernel size of 3x3. The median filtering to smooth an image, while preserving edges larger than the kernel dimensions in removing salt and pepper noise or speckle by replacing each center pixel with the median value within the neighborhood specified by the filter size (Castro and Donoho, 2009).

2.4.3. Accuracy check

The accuracy check was done by comparing the classification result with reference data that were believed to reflect the true land cover accurately. In this work, user’s,
producer’s, and overall accuracies together with kappa statistics were derived from
the error matrix.

The producer’s accuracy referred the fraction of correctly classified pixels with
regards to all pixels of that ground truth class. The user’s accuracy, referred to the
reliability of classes in classified images. The kappa statistic incorporated the
diagonal elements of the classification error matrix, and represented agreement
obtained after the elimination of the proportion of agreement that could have occurred
by chance. According to Landis and Koch (1977), Kappa values were grouped into
several categories. Values less than zero (0) indicated no agreement, 0-0.2 was
regarded as slight agreement, 0.21-0.40 were considered fair, 0.41-0.60 were
considered moderate, 0.61-0.80 were substantial, and 0.81-1 represented almost
perfect agreement.

2.4.4. Change detection

The post-classification change detection algorithm was used to determine the change
in mangrove from the three different classified images. It was comprised of
comparative analysis of independently produced classification maps on different
dates, via a mathematical combination of pixel by pixel. The output of this algorithm
was in the form of a matrix showing the initial parameter values of different land
covers on the columns, and their final state parameters along the rows, together with
their respective spatial representation images.

The procedure was carried out at two different intervals, for example, the change that
occurred during 1989-1998, 1998-2015, and finally from 1989 to 2015. This was
perhaps the most common approach to change detection (Jensen, 1996). It was successfully used by many researchers.
3. RESULTS AND DISCUSSION

3.1. Rice cropping systems

3.1.1. Wavelet analysis of time-series NDVI data

The DWT was applied to filter noise from the time-series NDVI data. In a study of rice crop phenology detection in Japan, the Coiflet wavelet (order 4) used in the wavelet transform has been demonstrated to give the best results among Daubechies wavelets (9, 13, 17) and Symlet wavelets (6, 12, 14) (Sakamoto et al., 2005). This Coiflet 4 was therefore selected and used in this case study for the decomposition of the time-series NDVI data. Figure 3.1, 3.2, 3.3, and 3.4 shows example of the DWT decomposition of a single rice (including single rice with shrimp culture and single rice with cultivation), double rice, and triple rice signature. The DWT using the pyramid algorithm (decomposition level 3) decomposed the signal into three fine-scale, \( (D_j) \), and large-scale information sets, \( (A_j) \).

In the DWT analysis, large scales correspond to a non-detailed view of the signal. As the scale increases, the finer components of the signal are retained in detail series and the smoother components (lower-frequency components) are given in an approximation series. The original NDVI time series and smooth NDVI time series of a single crop rice, double crop rice, and triple crop rice signature is shown in Figure 3.1, 3.2, 3.3, and 3.4.
Figure 3.1. The NDVI profile of single rice and shrimp culture signature before and after noise filtering.

Figure 3.2. The NDVI profile of single rice and cultivation signature before and after noise filtering.
For a scale $a = 2^3$, the periodic signal period is 88 days corresponding to the approximation components for level 3 ($A_3$). This approximation provided information about the seasonal variation of a rice crop in the study area over the considered period. The smooth curve shows the temporal pattern characteristics of the double rice cropping system throughout the year. The noise present in the

**Figure 3.3.** The NDVI profile of double rice signature before and after noise filtering.

**Figure 3.4.** The NDVI profile of double rice signature before and after noise filtering.
signature is significantly mitigated, therefore, this component was selected and used to discriminate rice cropping systems in the study area. Conversely, the two other detailed components (A_{1} and A_{2}), showing higher frequency components, and the three detailed components (D_{1},…,3), showing small-scale components of the signal, were discarded due to their temporal noise.

3.1.2. Temporal characteristics of rice crop NDVI profiles

In this section, an example of endmember extraction from the NDVI profile was discussed. There were distinctions between different rice cropping systems. Figure 3.5a shows the temporal evolution of NDVI intensity of single rice pattern. There was an apparent increase in the intensity of the greenness in the single crop rice system after the initial appearance of the crop (around DOY 193 or second week of July).

The levelling-off of the intensity indicated the end of the crop (DOY 361). There was an observable peak once a year related to the end of the crop. There were generally two peaks observed in a year for double rice cropping systems (Figures 3.5b) because the number of crops cultivated in the selected sample areas was two per year. The peaks would occur about 50-60 days after sowing. For instance, one could observe two peaks for the double rice cropping system. The NDVI values associated with this cropping system were extremely low after the second crop was harvested and became negative, because by that time, the floods had arrived so that the rice fields were covered by flood water.
Figure 3.5. Illustrative training patterns of rice cropping systems in the Mekong Delta: (a) single rice cropping system; (b) double rice cropping system; (c) triple rice cropping system.

The triple rice cropping systems similarly showed three peaks (Figures 3.5c) because three crops were practiced per year, where an extra crop could be added based on the availability of irrigation. The corresponding extra peak would appear either early or late in the year, depending on the area. The extra crop was indicated by the spring-summer crop. This crop was grown from March/April to May/June with its corresponding peak around DOY 113. The third (spring-winter) crop was hence grown from May to July. However, in areas with insufficient irrigation during the dry season and when the flood arrived late, the spring-winter crop would start from April to June, followed by the autumn-winter crop from July/August to October/December.

3.1.3. Classification results

The classification results for the 2002, 2005, 2010, and 2015 MODIS data using the Support Vector Machines are shown in Figures 3.6, 3.7, 3.8 and 3.9. The double rice
cropping was more concentrated in the upper region of the study area, while the triple rice cropping was mainly distributed in the middle of the study area between the Mekong and Bassac Rivers. The single and double rice cropping systems were common in coastal areas where there were irrigation difficulties and soils had major constraints for short-term rice cultivation.
Figure 3.6. Classification result of rice cropping systems in the Mekong Delta derived from the classification of the 2002 MODIS NDVI data using the Support Vector Machines.
Figure 3.7. Classification result of rice cropping systems in the Mekong Delta derived from the classification of the 2005 MODIS NDVI data using the Support Vector Machines.
Figure 3.8. Classification result of rice cropping systems in the Mekong Delta derived from the classification of the 2010 MODIS NDVI data using the Support Vector Machines.
Figure 3.9. Classification result of rice cropping systems in the Mekong Delta derived from the classification of the 2015 MODIS NDVI data using the Support Vector Machines.

As can be seen in the upper areas of the study area, from 2002 to 2015 the area under the double irrigated rice cropping system had been drastically converted to triple rice.
cropping systems. This conversion was due to the building of a ring-dyke system to protect the rice fields from the annual floods so that farmers living inside the ring-dyke areas could increase cropping intensity to three rice crops a year.

3.1.4. Accuracy assessment result

The error matrices of classification accuracy assessment for the year 2015 data using the Support Vector Machines was shown in Tables 3.1. A total of 1,500 pixels were randomly extracted from the ground truth image for accuracy assessment of the 2015 classification maps produced by the Support Vector Machines. The overall accuracy and Kappa coefficient were 82.5% and 0.73, respectively.

Table 3.1. Accuracy assessment results for the 2015 classification map archived by the Support Vector Machines.

<table>
<thead>
<tr>
<th>Ground truth (pixels)</th>
<th>Single rice</th>
<th>Double rice</th>
<th>Triple rice</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single rain-fed rice</td>
<td>355</td>
<td>85</td>
<td>60</td>
<td>500</td>
</tr>
<tr>
<td>Double irrigated rice</td>
<td>52</td>
<td>424</td>
<td>24</td>
<td>500</td>
</tr>
<tr>
<td>Triple irrigated rice</td>
<td>1</td>
<td>41</td>
<td>458</td>
<td>500</td>
</tr>
<tr>
<td>Total</td>
<td>408</td>
<td>550</td>
<td>542</td>
<td>1,500</td>
</tr>
<tr>
<td>Producer accuracy (%)</td>
<td>71.0</td>
<td>84.8</td>
<td>91.6</td>
<td></td>
</tr>
<tr>
<td>User accuracy (%)</td>
<td>87.0</td>
<td>77.1</td>
<td>84.5</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td></td>
<td></td>
<td></td>
<td>82.5</td>
</tr>
<tr>
<td>Kappa coefficient</td>
<td></td>
<td></td>
<td></td>
<td>0.73</td>
</tr>
</tbody>
</table>
The single and double rice cropping systems generally had lower producer accuracies. The reasons were that the sizes of rice fields of these two classes were generally small and scattered throughout the region. The effects of mixed pixel problems caused these small rice parcels to be easily omitted from the interpretation results. Moreover, the temporal confusion in discriminating between these two classes, and with other classes were especially observed in areas, such as the Long An province where the single rice cropping was integrated with other cash crops. The pattern of this rice-based cash crop cropping generally had more than one heading date per year. Thus, it was easily confused with other rice cropping patterns.

3.1.5. Summary of rice mapping results

From the results of rice crop phenology detection, the smooth time profiles reflected the temporal characteristics of rice cropping patterns throughout the year. This characteristic was important for understanding the temporal NDVI responses from different rice field cropping systems in the region.

The application of the Support Vector Machines to the filtered NDVI data confirmed the validity of the mapping method for quantification of rice cropping systems on a regional scale. In spite of existence of some error sources, partly due to temporal and spatial resolution of the MODIS sensors, the results obtained from this study were satisfactory, as shown by comparisons with the ground truth data.

The overall accuracy and Kappa coefficient achieved for 2015 were 82.5% and 0.73. The lowest per-class measure of producer accuracy were for the single and double rice classes, because these classes generally occupied small areas and were easily to
be temporally confused with other classes. Mixed pixel issues also exaggerated the commission of errors for the triple crop irrigated rice class.

### 3.2. Mangrove forests mapping results

The analyzing results of land use distribution which interpreted from Landsat data in 1989, 1998, and 2015 are presented in Figure 3.10, 3.11, and 3.12.

The classification results presented 11 major classes mapped, including mangrove forests, mix mangrove forests and shrimp, shrimp pound, agriculture, water bodies, sediment, mix built up area and perennials, other trees, cloud and shadow. The results showed that land covers have changed significantly in the study area by visual. Most of land conservation was mangrove and agriculture.

![Figure 3.10. Land cover result obtained from Landsat satellite in 1989](image-url)
Figure 3.11. Land cover result obtained from Landsat satellite in 1998

Figure 3.12. Land cover result obtained from Landsat satellite in 2015
For validation of the classification result, the ground reference map in 2014 was converted from vector data to raster data by using Polygon to Raster (with 30m resolution) function in ArcGIS. Then, a 100 random points was created each class to validate a classification result. The accuracy check was agreed when compared with classification results and the ground truth data with overall accuracy was 77.4% and kappa coefficient was 0.68 in 2015.

3.2.1. Spatial distribution of mangrove forests

Spatiotemporal distribution of mangrove showed for three particular years of 1989, 1998 and 2015 in Figure 3.13, 3.14 and 3.15.

![Spatial distribution of mangrove derived from Landsat data in 1989.](image)

**Figure 3.13.** Spatial distribution of mangrove derived from Landsat data in 1989.
Figure 3.14. Spatial distribution of mangrove derived from Landsat data in 1998.

Figure 3.15. Spatial distribution of mangrove derived from Landsat data in 2015.
Mangrove in the area was concentrated in the coastal estuaries, and rivers where interlinked between land and the sea. The main concentration was located in Ngoc Hien district with high dense of mangrove. The result of classified maps in 1989, 1998, and 2015 showed that the total mangrove areas were 519.12 km\(^2\) (20.85%), 283.05 km\(^2\) (11.68%), and 630.03 km\(^2\) (26.37%), while the mix mangrove and shrimp area were 425.84 km\(^2\) (17.10%), 802.53 km\(^2\) (33.13%), and 897.34 km\(^2\) (37.56%), respectively (Figure 3.16). This area was strictly managed by the local governments as natural reserves for biodiversity conservation. Mangrove in the upper part was relatively fragmented due to the development of shrimp culture. The study area showed significant rates of mangrove loss in the upper part of the Ca Mau peninsula, largely due to conversion to agriculture.

![Graph showing mangrove and mix mangrove and shrimp areas](image)

**Figure 3.16.** Real estimation of mangrove and mix mangrove and shrimp during the past three decades.
3.2.2. Mangrove change detection results

Changes in mangrove in difference periods were analyzed and are shown in Figure 3.17, 3.18, and 3.19 as well as Table 3.2. The mangrove cover in Ca Mau peninsula has significantly changed during the past three decades. Mangrove has been reduced rapidly due to shrimp culture and deforestation for wood construction and fuel. From 1943 to 1993, mangrove was destroyed by the war and other human activities such as cutting down for firewood and converting to paddy fields (Hong and San, 1993), but from 1998 to 2015 reduction of mangrove was contributed by shrimp farm activities. In the results, most land use was covered to mix mangrove and shrimp culture as well as aquaculture. Mangrove has been subjected to enormous pressures and threats within past three decades. The loss of mangrove from 1989 to 2015 was approximately 230.7 km$^2$ (9.5\% of the total area) (therein, converted to mix mangrove and shrimp was 3.7\%), while 11.3\% (277.4 km$^2$) was recovered or newly planted at the same time. The conversion of the other land uses to mix mangrove and shrimp significantly increased by 25.4\% of the total area (619.6 km$^2$) (Table 3.2).

**Table 3.2.** Change in mangrove from 1989 to 2015

<table>
<thead>
<tr>
<th></th>
<th>1989</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mangrove</td>
<td>Mix Mangrove-shrimp</td>
</tr>
<tr>
<td></td>
<td>km$^2$</td>
<td>%</td>
</tr>
<tr>
<td>Mangrove</td>
<td>288.6</td>
<td>11.8</td>
</tr>
<tr>
<td>Mix Mangrove-shrimp</td>
<td>125.1</td>
<td>5.1</td>
</tr>
<tr>
<td>Others</td>
<td>152.3</td>
<td>6.2</td>
</tr>
</tbody>
</table>
Although reforestation areas were 11.3% (therein mangrove had newly formed from sediment area about 6%) of the total mangrove areas, they demonstrated strategies of reforestation were noted in Ca Mau peninsula before 2000. As a result, the area of mangrove in the study has only 283.05 km\(^2\) in 1998 and covered 11.68% of the total land area. Although there are factors affecting the analysis of remote sensing image results in identification of mangrove, such as images covered by cloud and data outside image area of mangrove in 1998 could be higher than 283.05 km\(^2\). In addition, together with results of data analysis, a part of mangrove areas with low density were areas of mixing between mangrove with shrimp culture or mangrove with canal.

Further, changes of mangrove came from not only deforestation but also from replanting in some areas. These two activities, including deforestation and reforestation, occurred seemingly at the same time. Therefore, in 1998 - 2015 period, replanting activities and new formed mangrove were noted and improved more than before the period. In addition, some areas of mangrove were unchanged but their quality was changed (density of mangrove). Most these unchanged areas were located in conversation parts or mangrove biosphere areas such as Dat Mui and Cham Chim Park. Analysis results showed that the replanting activities occurred in the mud flat of the western coasts by nature and people while in the eastern coast the erosion has happened. This was also demonstrated by the results of study on changes of coastline recently (Hieu et al., 2000). Besides restoring mangrove, the purpose of replanting was also the expansion of land use into the west sea. The replanting occurred after the deposition of sediment and the shallow seabed.
Figure 3.17. Changes in mangrove forests in the study area in 1989-1998.

Figure 3.18. Changes in mangrove forests in the study area in 1998-2015.
From above analysis, although some areas of mangrove were replanted, mangrove in study area have been decreasing both in quantity and quality. There are many factors, which degraded mangrove, but the major one was shrimp culture activities. Other factors such as transformation, industry, urbanization, degradation of environment and sedimentation also impacted mangrove changes. These factors also had relationship with one another. On the contradictory, shrimp culture, on one hand, supplied nutrient salts for mangrove based on water and sediment discharge into mangrove areas. On the other hand, farmers have cut down mangrove and conversed to shrimp farms. Further, because of lack of information on environmental conditions, shrimp culture techniques and financial resources, shrimp culture failed in some areas or shrimp ponds were only used in a short period (Hong, 1995). After few years, land
has been degraded and farmers continued to cut down mangrove to make new shrimp ponds.

The attitude of mangrove destruction and degradation was based on short-term exploitation for immediate economic benefit, rather than longer-term but sustainable exploitation. These are major causes of mangrove deforestation in the period of 1989 - 1998. However, human activities impact mangrove forests. Transportation increased suspended sediment. Agriculture also increased soil acidification and agrochemical in water but agricultural production has low values (Hong and San, 1993). These chemicals impacted negatively on shrimp farms and mangrove forests (Hong, 1995). In addition, other demand activities also caused conflicts of natural resources users and then affected mangrove forests. Beside of shrimp culture, huge areas of mangrove forests have been lost due to wood extraction, conversion to agriculture or salt production, coastal industrialization and urbanization and the war, but these areas have been equaled to mangrove forest areas where shrimp farming has been blamed for large scale losses.

3.2.3. Summary of mangrove forest mapping results

From the results of mangrove forests mapping, it is proved that application of the Support Vector Machines could be done in local scale and the method can be extended to the region or transfer to the other study area.

Validation was made by comparing the classification result with the ground reference data, which yielded agreement with overall accuracy 77.4% and Kappa coefficient of 0.68. The results showed that mangrove has decreased by half (236.07 km²) from
1989 to 1998 due to shrimp culture. At the same time, the area of mix shrimp and mangrove increased by 386.69 km² (about 88%). However, mangrove and mix mangrove, and shrimp areas have been raised by twice for mangrove and about 11% for mix mangrove and shrimp, respectively, in the second period from 1998 to 2015. These threat factors appeared to be regional in two cases of the study from natural to human-made factors with mangroves in the upper western coasts, from natural factors mainly of drought and salt intrusions, and wood for construction. In addition, these changes were mainly attributed to the development of aquaculture. Shrimp culture was especially identified as a major cause of direct and indirect loss of mangrove ecosystems due to deforestation for pond construction.

3.3. Long term water balance in the Mekong delta

Evapotranspiration, which is the water transferred from land to the atmosphere via surface evaporation and plant transpiration, links the terrestrial water, carbon, and surface energy exchanges (Wang & Dickinson, 2012). It provides the atmospheric moisture that eventually returns to the surface as rain or snow and also consumes an enormous amount of heat, which helps to cool the land surface (Bonan, 2008). Therefore, accurate knowledge of the temporal and spatial variations in evapotranspiration is critical for understanding the interactions between land surfaces and the atmosphere (Keane et al., 2002), improving water resource management (Meyer, 1999 and Raupach, 2001) and for investigating drought occurrence and impact. However, evapotranspiration remains the most problematic component of the water cycle because of the heterogeneity of the landscape and the large number of
controlling factors involved, including climate, plant biophysics, soil properties, and topography (Friedl, 1996).

Recently, numerous methods have been developed to estimate terrestrial ecosystem evapotranspiration, but inter-comparisons of global evapotranspiration estimates have revealed large model uncertainties. Moreover, the uncertainties in global land evapotranspiration from multiple remote sensing methods, land surface models and reanalysis, are close to 50% of total annual mean values.

Satellite-based observations of land surface and atmospheric properties provide the most spatio-temporally consistent and direct estimates of land surface, if used appropriately in physically accurate and statistically robust models. Some physical process evapotranspiration models have been developed based on the Penman–Monteith (Yuan et al., 2010). However, some of the process-based evapotranspiration models are limited by their requirements for extensive parameterizations of highly variable factors such as the maximum stomatal conductance and soil water content. The relatively large uncertainties in these models pose a challenge for the accurate assessment of evapotranspiration. Therefore, empirical regression models have been used to upscale eddy covariance measurements (Zhou et al., 2008). In this study, the evapotranspiration model such as modified Penman, Thornthwaite and NDVI was applied to predict evapotranspiration during the study period. The primary objectives of this study are: (i) to determine evapotranspiration in the Mekong delta from 2000 to 2015 using multi-satellite data; and (ii) to identify changes of water resources in the same period.
3.3.1. Water balance change

Water balance is based on the law of conservation of mass: any change in the water content of a given soil volume during a specified period must equal the difference between the amount of water added to the soil volume and the amount of water withdrawn from it. In principle, a water balance can be computed for any soil volume, ranging from a small sample of soil to an entire catchment.

Inputs to the model are temperatures (T, in degrees Celsius), precipitation (P, in millimeters), and the latitude (in decimal degrees) of the location of interest. The latitude of the location is used for the computation of day length, which is needed for the computation of potential evapotranspiration (PET). The model is referred as the Thornthwaite model. Discussion of the individual components of the water balance follows.

The FAO-PM equation recommended for daily evapotranspiration (mm/day) estimate may be written as,

\[
ET_o = \frac{0.408\Delta(R_n - G) + \gamma(900/(T + 273))u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}
\]  

where \( R_n \) is the net radiation at the crop surface (MJ m\(^{-2}\) day\(^{-1}\)), \( G \) the soil heat flux density (MJ m\(^{-2}\) day\(^{-1}\)), \( T \) the air temperature at 2 m height (°C), \( u_2 \) the wind speed at 2-m height (m s\(^{-1}\)), \( e_s \) the vapor pressure of the air in saturation (kPa), \( e_a \) the actual vapor pressure (kPa), \( \Delta \) the slope of the vaporessure curve (kPa °C\(^{-1}\)), and \( \gamma \) is the psychrometric constant (kPa °C\(^{-1}\)). A complete set of equations is proposed by Allen et al. (1998) to compute the parameters of Eq. 4.1 according to the available weather
data and the time step computation, which constitutes the so-called FAO-PM method. $G$ may be ignored for daily time step computation.

### 3.3.2 Climate data analysis results

Comparison of the long-term annual precipitation (Figure 3.20) at Can Tho station from 2000 to 2014 shows that long-term trend of precipitation was decreased during the research periods. The yearly average rainfall in the Mekong Delta is 1496 mm and concentrates mainly in the rainy season (from May to November). The highest average rainfall (1911 mm/yr) occurred in 2000 and the lowest average rainfall was 1396 mm/yr in 2013. Normally, October, which has the highest rainfall, is the period of flood peaks in the Mekong Delta and also of water level rise due to Chuong wind.

![Graph showing long-term precipitation at Can Tho station, Mekong Delta.](image)

**Figure 3.20.** Long-term precipitation at Can Tho station, Mekong delta.

From January to March, the average rainfall in this area is very low. Sea water level rises due to wind surges during this dry period can lead to drought spells and salt intrusion that may severely affect agriculture. The combination of heavy rainfall,
drought and water level rise due to wind and the occurrence of flood peaks important issues which need special consideration in climate change coping and adaption strategies for the Mekong Delta.

**Figure 3.21.** Long-term temperature at Can Tho station, Mekong delta.

Statistical results of average temperature change in the study areas are presented in Figure 3.21. The statistical results indicate that average temperature in the Mekong Delta in has increased. For the whole year, the average temperature change of the Mekong Delta in the period 2000 - 2014 is 0.02°C. Seasonally, temperature change in the dry season is higher than the rainy season. This is mainly the effect of rainfall increase during the rainy season which has a temperate effect on temperatures.

**3.3.3 Long term water change**

In the period 2000 to 2014, total evaporation in the Mekong delta predicted with the Penman-Monteith was 2500 mm/yr. Period with the highest evaporation was from February to April, which are also with low humidity and high temperature. During
the rainy season, due to high air humidity and lower temperature, the evaporation is low.

**Table 3.3.** Evapotranspiration estimated from Penman modified by Thornthwaite

<table>
<thead>
<tr>
<th>Land used</th>
<th>Ratio</th>
<th>Evapotranspiration (mm/month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>0.2</td>
<td>24</td>
</tr>
<tr>
<td>Residence</td>
<td>3.8</td>
<td>41</td>
</tr>
<tr>
<td>Grass</td>
<td>23</td>
<td>83</td>
</tr>
<tr>
<td>Paddy Field</td>
<td>0.3</td>
<td>94</td>
</tr>
<tr>
<td>Agricultural Field</td>
<td>6.2</td>
<td>88</td>
</tr>
<tr>
<td>Bare Soil</td>
<td>1.2</td>
<td>67</td>
</tr>
<tr>
<td>Forest</td>
<td>57</td>
<td>79</td>
</tr>
<tr>
<td>Water</td>
<td>0.1</td>
<td>101</td>
</tr>
</tbody>
</table>

**Figure 3.22.** Evapotranspiration estimation in the Mekong delta from 2000 to 2014.

The table 3.3 shown that evapotranspiration estimated for different land used. As the table presented, water bodies has the lowest ratio (0.1) but it had highest evapotranspiration (101 mm/month), follow by paddy field with ratio was 0.3 and
evapotranspiration was 94 mm/month, and the lowest evapotranspiration was urban and resident was 24 mm/month and 41 mm/month, respectively.

In addition, the correlation between NDVI and evapotranspiration was analyzed for 2015. Figure 3.23 shown that NDVI and evapotranspiration had linear correlation with $R^2$ was 0.82. It is demonstrated that with high NDVI value (forest, paddy field), the evapotranspiration was high. In contrast, urban or president had a low evapotranspiration based on characteristics from itself. In wet seasons precipitation was greater than evapotranspiration which creates a water surplus. Ground stores fill with water which resulted in increased surface runoff, higher discharge and higher river levels. This means there was a positive water balance. In drier seasons evapotranspiration exceeded precipitation. As plants absorb water ground stores were depleted. There was a water deficit at the end of a dry season.

![Graph showing the correlation between evapotranspiration and NDVI.](image)

**Figure 3.23.** Correlation between evapotranspiration and NDVI in 2015.
Figure 3.24 shows that the estimation of runoff was decreased by 28 mm/yr on average. Runoff is the greatest in the wet season from May to October, and low in the remaining months, following the pattern of monthly precipitation distribution for the basin. Clearly the impacts of projected changes in climate have to be considered. Irrigation systems will need to be designed to deliver increased amounts. Dam storages may need to be increased to meet increased irrigation withdrawals. The capacity for hydropower generation is likely to be increased across the basin, the return systems should be designed to capture the likely capacity for power generation. Dam design will have to take into account changing probabilities of rainfall and runoff events of different magnitudes.

Figure 3.24. Runoff estimation in the Mekong delta from 2000 to 2014.
4. CONCLUSIONS

This section presents a general discussion of the research findings. Advantages and disadvantages of the algorithms used for classifying rice cropping systems and mangrove forests mapping in the study area were also addressed in great detail. Sets of conclusions were then drawn based on the research findings. Finally, the chapter points out possibilities for further investigations based on the results and conclusions.

4.1. General discussion

The research was conducted in the Mekong Delta, Vietnam using MODIS (from 2002 to 2015) and Landsat data (from 1989 to 2015) to address the following two objectives: 1) to detect rice cropping systems, and 2) to monitor and analyze spatial distribution of mangrove forests during the past decades.

For rice crop phenology detection, the wavelet transform (using Coiflet 4) was used for filtering noise from the time-series NDVI data. The smooth time profiles extracted from the filtered data were used for detecting phenological dates (sowing and harvesting dates) of rice crops.

The Support Vector Machines were applied to the filtered time series NDVI data as well as Landsat imageries. The classification results were validated with the ground truth data, indicating that this method was promising not only for mapping rice cropping systems, mangrove forests cover but also for the other object of land use in the study area. It was noted that the classification accuracy levels are greatly dependent on the proper selection of training patterns that will be trained in the Support Vector Machines for classification.
Although the Support Vector Machines have been demonstrated to give a good results, it still has some disadvantages. For example, the kernel choice and kernel specific parameters (C and \( \gamma \)) affect the accuracy classification level achieved. In this study, the choice of RBF kernel for classification was made based on existing literature. Nevertheless, further studies should be carried out to determine the effects of kernels and their associated parameters on the classification performance using optical remote sensing data.

**5.2. Conclusions**

In case of rice crop mapping, the ultimate goal of this study was to map rice cropping systems in the Mekong Delta using MODIS data from 2002 to 2015. Rice cropping systems were classified using the 2002, 2005, 2010 and 2015 time-series MODIS 250 m NDVI data. The time-series data were first filtered with the Wavelet transform. The Support Vector Machines was then applied to the filtered data for classification of rice cropping systems in the study area.

The overall accuracy and Kappa coefficient produced for the year 2015 data were 82.5% and 0.73. The double rice cropping was more concentrated in the upper region of the study area, while the triple rice cropping was mainly distributed in the middle of the study area between the Mekong and Bassac Rivers. The single and double rice cropping systems were common in coastal areas where there were irrigation difficulties and soils had major constraints for short-term rice cultivation.

In case of mangrove forests mapping, this research successfully applied a method to map the distribution of mangrove forests in the Mekong Delta. In addition, mangrove
forests was extracted based on characteristics, singularities, and distribution as well as reflectance values and spectral properties of mangrove forest in the images. The classification results indicated satisfactory agreement with the ground reference data with overall accuracy of 77.4% and Kappa coefficient of 0.68. After 26 years, mangrove forest lost more than 9% of the total area due to land use conservation and coastal erosion, but more than half of mangrove forest, which has existed, was low density. In addition, mangrove was recovered or newly planted by 277.4 km² (11.3%) at the same time.

These changes of mangrove forests were affected by two activities: deforestation and replanting but capacity of planting. The major reason of recent mangrove changes was shrimp farm development. Shrimp farm development and degradation also caused environmental and natural resource problem as well as socio-economic aspects. Reforestation of ineffective shrimp ponds might be a good solution to improve the sustainability of this ecosystem before one can make a master plan of land uses for the coastal zone to help solve these problems.

From these analysis results, it can be seen that the method used in this research was successfully applied to detect long-term water balance in the Mekong delta. The results was found that long term air temperature and evapotranspiration were increased by 0.02°C/yr and 0.3mm/yr, respectively while precipitation and runoff were decreased by 27mm/yr and 28mm/yr, respectively. In addition, land cover changed by 1.1% to 11.9% from 2000 to 2015 and land use control is very important in the study area. For a long term water balance, runoff was decreasing due to land cover changed in the Mekong delta and the other manmade factor in the upstream.
This was a main cause that directly affected on water resource management. The overall efforts in this study demonstrated the effectiveness of the proposed method used for detecting changes of long-term water resource, improving the ability to capture spatial variability of water demands in the basin. Hence, future agricultural and other economic sectoral development plans for the Mekong delta should be formulated with the additional objective to save water. Because of climate change effects, the sea level rise, upstream agricultural development, upstream water diversions and unfavorable upstream reservoir operation will cause more acute water shortages and more salinity intrusion for the Mekong delta.

5.3. Future research

The algorithms used in this study have demonstrated to give good results for rice crop mapping and forests mapping in the study area. The algorithm for rice crop mapping could be extended to identify crop growing areas and monitor surface soil moisture in the region. In addition, this research provide nice information on identifying growing stages on rice crop. Based on this information, the yield of rice can be estimated by using regression model. Besides, soil surface moisture can estimated from MODIS data and it is a good candidate for detecting drought that is effected on rice cropping system under climate change conditions.

In case of forests mapping, the current trends of mangrove loss can be rapidly slowed with the establishment of good management practices, legislation and clear frameworks for ownership and used. The right economic settings and incentives for
improved management and conservation will only be created if the true value of mangroves is recognised.

For mangrove management to tackle the diverse drivers of loss, appropriate strategies should be incorporated into wider planning and policy frameworks involving all relevant agencies and stakeholders across the linked ecosystems. A clear decision and management structure involving all stakeholders needs to be established to reconcile the different services and use of mangroves. Local or customary tenure rights should be a key element in management planning.

Mangrove ecosystems play a large role in climate regulation, food security and poverty reduction, strategies and actions for their conservation and sustainable use must be integrated within broader development planning frameworks. These frameworks include national development and poverty reduction strategies, fisheries and forestry action plans, as well as pre-emptive policies such as natural disaster risk reduction management plans and climate change adaptation strategies.

Governments must recognize the strong link between mangrove ecosystem degradation and persistence of poverty in many rural coastal communities. Sustainable management and restoration of mangrove ecosystems is an achievable and cost effective mechanism that can contribute, in many countries. Coordinated action on mangroves needs to be ensured within the international policy agenda as well as under the different biodiversity, wetlands, sustainable development and climate change agreements.
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