Factors Affecting Drinking Water Security in South-Western Bangladesh

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for the children of Bangladesh,
with hope for a brighter future

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CHAPTER 1

Introduction

1.1 Overview

In the past century, rates of water usage have grown twice as rapidly as global population [FAO 2007; UN, 2013]. Although global renewable freshwater resources are currently sufficient to meet population requirements, uneven distribution of water resources, compounded by pollution and mismanagement, results in severe national and regional disparities in water availability and quality [UN, 2013]. These circumstances bring into question the state of *water security* from a global perspective down to the individual level. There are many definitions of water security, but this is one of the most comprehensive:

> *'the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability' [UN-Water, 2013, p. 1]*.

Water security is a diverse topic, partially because of the wide range of scales at which it is relevant, and the units of analysis that are necessary [Wouthers, 2010; Cook & Bakker, 2012]. Information about water security is also difficult to synthesize because of the various scales of data collection. Different disciplines studying water security tend to use different scales, e.g., hydrologists focus on watersheds, and social scientists study communities [Cook & Bakker, 2012].

Water security assessed at the national level is inconsistent with the fact that most water management is conducted at the basin level or lower [Lautze & Manthrithilake ,2012]; what Bakker [2012] calls the "*scalar mismatch*". Bakker [2012] further states that most of the academic research to date on water security has been poorly integrated with the needs of water practitioners and policy makers, and thus changes are required for research to make a meaningful contribution to the global water crisis. Bakker [2012] opines that analysis in the field of water security "…*requires interdisciplinary, collaborative research, transcending 'broad' versus 'narrow' and 'academic' versus 'applied' distinctions…*" [p. 915].

1.2 Study Area

Bangladesh provides an acutely relevant area in which to study water security, due to its many developmental and environmental challenges. Bangladesh is the largest of the "least developed countries", and is one of the world's most densely populated and impoverished countries [Ravenscroft, 2003]. As such, it is encumbered with the associated strains on its natural resources. Bangladesh is primarily rural and agricultural, and is one of the world's most rapidly growing countries [Ravenscroft, 2003; FAO, 2013].

Bangladesh is a low lying deltaic nation, located in one of the world's largest floodplains: that of the Ganges, Brahmaputra, and Meghna rivers [Ravenscroft, 2003; FAO, 2013]. Bangladesh is extremely vulnerable to water shocks, including floods, cyclones and storm surges [van Schendel, 2009; FAO, 2009]. Water plays an essential role in the lives of many people in Bangladesh, especially in rural areas; water is intrinsically linked to livelihoods in agriculture, fisheries, navigation, forestry, and aquaculture [Ravenscroft, 2003; FAO, 2013]. More than 90% of Bangladesh's surface water originates in other countries, which inhibits the country's ability to manage its rivers at the watershed level [Chowdhury, 2010]. There is only one multi-purpose dam in the country, and three barrages exist that are used for irrigation. In addition, India controls flow from the Ganges River into Bangladesh by means of the Farraka Barrage, which is under a transboundary treaty for its flow rate during the dry season [FAO, 2013].

Bangladesh has a tropical monsoonal climate; the monsoon ensures plentiful rainfall, but only for a few months of the year (June-September), when most of the yearly precipitation occurs [FAO, 2009; Chowdhury, 2010; K. Ahmed, 2011] The spatial distribution of rainfall is highly variable throughout the country, and there is insufficient storage throughout the country to meet the needs of people and agriculture during the dry season [Ravenscroft, 2003, FAO, 2009; Ansari, et al., 2011; K. Ahmed, 2011; FAO, 2013]. Approximately 80% of the total water withdrawal in Bangladesh is from groundwater, with agriculture comprising the greatest sector water withdrawal (88%) [FAO, 2013]. Lack of safe drinking water is of primary concern in

Bangladesh due to microbial surface water contamination, as well as the presence of arsenic and salinity in groundwater wells [Ravenscroft, 2003; Ahmed, et al., 2004; 2011 ; Chowdhury, 2010, Khan & Kumar, 2010; Mondal, et al., 2013; FAO, 2013].

Rice cultivation is the most important activity in the nation's economy, and one of the biggest uses of water [FAO, 2013; Chowdhury, 2010]. The use of groundwater for irrigation has become increasingly important due to demand for irrigation during the dry season, and the limited availability of surface water [Ravenscroft, 2003; FAO, 2013].

An important part of the water infrastructure system is the coastal embankment program in the south-west portion of the country, initiated in the 1960s. Embankments were constructed to increase agricultural production, to protect agricultural land (*polders*) from floodwaters, and to reduce risks to people from water-related hazards [Islam, 2006; A. Ahmed, 2011; FAO, 2013; Auerbach, et al., 2015]. Although the embankments have led to increased agricultural production, over time they have also contributed to significant adverse impacts to the environment [Mondal, et al., 2013; Auerbach, et al., 2015; Rasul & Chowdhury, 2010]. Most of the southern coast is within 1 to 3 m of the mean sea level [Mondal, et al., 2013]. Due to its low elevation and flat topography, potential climate change impacts, especially sea level rise, are of great concern in Bangladesh [FAO, 2009; Chowdhury, 2010; Mondal, et al., 2013].

South-west coastal Bangladesh is the region of interest for this research **[Figure 1.1].** This area is particularly susceptible to environmental stresses because of its highly exposed coast and proximity to the Bay of Bengal, located 60 km to the south. The coastal area occupies 32% of the land area of Bangladesh, and is home to 28% of the total population [Ahmed, 2011]. Shrimp farming has intensified over the past two decades, thereby greatly changing the local landscape [Islam, 2006; Datta, et al., 2010].

In the Khulna District, there are 14 upazilas that are considered coastal [Uddin & Kaudstaal, 2003]. The local area of interest for fieldwork is "Polder 32" (P32), which is in the Dacope upazila of the Khulna District of south-west Bangladesh. Polder 32 is surrounded by tidal rivers and other polders, and is bordered by the Sundarbans National Park to the south. Polder 32 is approximately 19 x 7 km in size, and has about 44,000 residents [BBS, 2012].

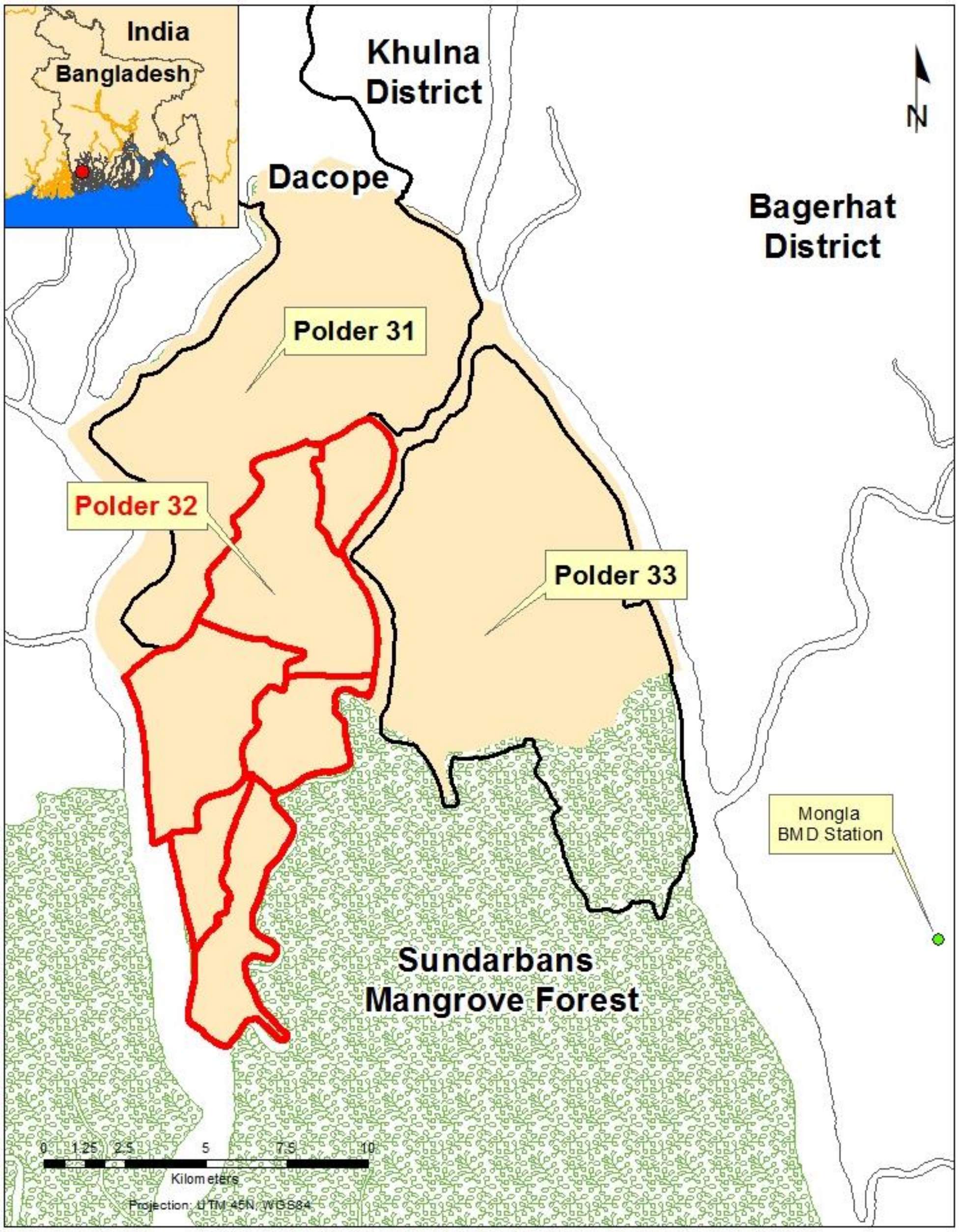

Figure 1.1. Location of Study Area

1.3 Research Objectives

The overall goal of the research is to provide an assessment of the factors that contribute to drinking water security in a rural community within a developing nation in the face of increasing global water scarcity, and how that assessment is affected by geographical scale. The research is based on the premise that a comprehensive assessment of water security requires a transdisciplinary approach; therefore, environmental data will be integrated with available socioeconomic factors to evaluate water security in a holistic way.

This goal was realized by accomplishing the following three research objectives:

1. *Evaluate and describe Bangladesh's level of water security based on a national scale, using existing water indices and data.*

2. *Characterize the elements of local water security, drinking water access and quality, using field-measured data and local social data*.

3. *Evaluate area land use change using remote sensing***.**

In this context, Polder 32 may serve as a surrogate for assessing other environmentally vulnerable areas, and the research may point to certain parameters that have the potential to serve as indicators for water security in other geographical areas, and at different scales. Although it is recognized that military and political conflicts, natural disasters, and the assessment of risk, vulnerability, resilience and sustainability of communities greatly affects water security, these topics are not directly addressed as part of this research.

1.4 Structure of Dissertation

The work presented in this dissertation is organized as three separate but related manuscripts, reflecting an interdiscplinary approach to assessing the factors that contribute to water security in southwestern Bangladesh. Each manuscript has its own methods and references; therefore, these sections were not combined in an effort to reduce redundancy in this dissertation.

In the first task, water indices that describe various aspects of water security on a national level were considered. As described in Chapter 2, this was accomplished using a case study approach to examine the application of water indices to two small, Asian countries with very different levels of water security, Bangladesh, and Sri Lanka [Gunda, et al. 2015]. Approaching water security in this way provided an overview of the parameters that are most influential in assessing water security at the national level by use of indices, as well as a description of the conceptual evolution of water security. In Chapter 3, the results of an interdisciplinary investigation employed to evaluate the critical elements of local water security is presented. This was accomplished by performing fieldwork at Polder 32 that included groundwater and surface water quality sampling; the evaluation of barriers to drinking water access; and implementation of an ethnosurvey at selected communities on Polder 32 [Benneyworth, et al. 2016]. In Chapter 4, remote sensing techniques were used to address land use change at Polder 32 that might contribute to local water security. Finally, Chapter 5 provides a summary of the research contributions of this dissertation and ideas for potential future work.

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CHAPTER 2

Exploring Water Indices and Associated Parameters: A Case Study

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ABSTRACT

In the past twenty years, over 50 water indices have been developed to characterize human-water systems within the frameworks of water scarcity, water poverty, water vulnerability, and water security. This study compares existing water indices in Bangladesh and Sri Lanka to better understand which parameters (or lack thereof) contribute to the usefulness of water indices. Drawing on knowledge about human-water interactions in Bangladesh and Sri Lanka, this exploration of indices at the parameter level highlights missing parameters, inadequate consideration of complex relationships among parameters, and inconsistencies in index nomenclature and units. This study reveals both the benefits and shortcomings of water indices and provides recommendations for researchers and water managers to consider when selecting indices to assess and support their water policy goals.

2.1. Introduction

In the past century, rates of water usage have grown twice as rapidly as global population [FAO, 2007; UN, 2013a]. Although global renewable freshwater resources are currently sufficient to meet population requirements, uneven distribution of water resources, compounded by pollution and mismanagement, results in severe national and regional disparities in water availability and quality [UN, 2013a]. Considering the influence of human management on the distribution of water resources, it is important to study both the physical and human aspects to develop a comprehensive understanding of water systems (hereafter referred to as 'human-water systems').

Human-water systems were initially viewed through the lens of 'water scarcity', which assessed the amount of water physically available to a nation [Falkenmark, 1989]. However, this traditional definition of water scarcity does not consider the capacity of a nation to adjust to limited water resources [Appelgren & Klohn, 1999]. Consequently, the framework expanded to 'water poverty', which assesses both the physical and economic capabilities of a nation to meet its water needs. External threats to the human-water system (e.g. extreme weather events) were incorporated into the framework through 'water vulnerability'. Most recently, interactions between humans and water have been viewed comprehensively in terms of 'water security'. UN-Water defines water security as:

> *'the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability' [UN-Water, 2013, p. 1].*

In the past 20 years, over 50 indices have been created to measure human interactions with water [Plummer et al., 2012]. These indices facilitate program evaluation, support environmental monitoring, and serve as tools for managers of human-water systems [Chenoweth, 2008]. Indices vary in both comprehensiveness and focus, reflecting the expanding scope of the frameworks [Rijsberman, 2006]. Literature reviews of existing water indices have been conducted by various authors [Chenoweth, 2008; Brown & Matlock, 2011; Cook & Bakker, 2012; Plummer et al., 2012]. However, little attention has been given to which parameters (or lack thereof) contribute to the usefulness of water indices. Therefore, we use a case study approach to assess existing water indices and parameters for two countries in South Asia, a region exposed to extreme seasonal and spatial variation in rainfall, among other water-related stressors [Rijsberman, 2006; Grey &Sadoff, 2007; ADB, 2013a]. Since the scale and scope of water indices vary greatly, we limit our analysis to national water indices that are flexible enough to be employed at sub-national scales. Our aim is not to review these two countries' water policies but rather to systematically evaluate tools often used in policy setting. We conclude with recommendations for researchers and water managers to consider prior to selecting and applying indices to achieve their particular national water goals.

2.2. Methods

In this study, an 'index' is computed from multiple parameters and a 'parameter' is defined as a value that is measured or observed. Some parameters are also computed using multiple values;

additional information regarding these parameters is presented in the following sections. The various parameters relate to different aspects of water resource issues. For example, river flows and groundwater volumes can be taken as measures of water availability whereas the availability of piped water and the proximity of households to wells can be taken as measures of access. We group like parameters together and refer to the groups as 'components'.

2.2.1 Index Descriptions

Multiple water indices in the current literature were reviewed. Only national indices for Sri Lanka and Bangladesh that have already been developed or could be developed given readily available information were included in the analysis. Indices were grouped under frameworks based primarily on their nomenclature. The indices included in this study are: the Falkenmark indicator [Falkenmark, 1989], the social water scarcity index [Appelgren & Klohn, 1999], the water poverty index [Lawrence et al., 2002], the rural water livelihoods index [Sullivan et al., 2009], the index of drinking water adequacy-2 (IDWA-2) [Kallidaikurichi & Rao, 2009], the national water security index [ADB, 2013a], the water security index [Lautze & Manthrithilake, 2012], the water resources vulnerability index [Raskin et al., 1997], and the composite water vulnerability index [Paladini, 2012].

2.2.1.1 Water Scarcity. The Falkenmark indicator identifies regions as being under 'water stress' when less than 1,700 cubic meters (m^3) of water are available per capita per year; regions are 'water scarce' when only 1,000 m^3 of water are available per capita per year [Falkenmark, 1989]. The Falkenmark indicator is unique because it is an index containing only a single parameter; the index is defined simply as water resources per capita. This traditional definition of water scarcity is based on physical resources (i.e. total water resources available to a country and its population size) and gives no consideration to the societal response capacity of a nation to adjust to the scarcity situation. In response to these criticisms, Appelgren & Klohn [1999] attempted to account for this societal capacity by dividing the Falkenmark indicator by the human development index (HDI), a composite index that is composed of national parameters for education, health, and income [UNDP, 2013a]. They argued that this new index, called the 'social water scarcity index', reflected the social and institutional capacity of a country to respond to water stress.

2.2.1.2 Water Poverty. 'Water poverty' links physical estimates of water availability to socio-economic variables that reflect conditions of poverty [Feitelson & Chenoweth, 2002; Lawrence e et al., 2002; Sullivan, 2002; Sullivan & Meigh, 2003; Sullivan et al., 2003]. Water poverty indices account for the fact that many countries with adequate physical water resources lack the political and financial resources necessary to make these resources available [Seckler et al., 1998; Molle & Mollinga, 2003; Rijsberman, 2006; Molden, 2007]. The most commonly used index in this framework is the water poverty index (WPI). This index includes five components of water poverty: resources, access, capacity, use, and environment [Lawrence et al., 2002; Sullivan, 2002]. The water poverty index encompasses not only water and income parameters but also parameters regarding ecosystem productivity and human health [Lawrence et al., 2002; Sullivan, 2002; Brown & Matlock, 2011].

In 2009, Sullivan et al. [2009] introduced a version of the WPI for rural communities called the 'rural water livelihoods index', which distinguishes between urban and rural human-water systems. The rural water livelihoods index includes components accounting for access to water and sanitation, crop and livestock water security, and clean and healthy environments, as well as secure and equitable water entitlements. This index also utilizes parameters measuring local corruption, agricultural holdings, and water quality (total nitrogen consumed on cultivated land) [Sullivan et al., 2009].

Biswas & Seetharam [2008] simplified the WPI to create an index of drinking water adequacy (IDWA). The first version of IDWA, IDWA-1, was an aggregate of internal renewable freshwater resources, access to improved water sources, national capacity to purchase water (represented by nominal gross domestic product (GDP)), domestic water use, and water quality (represented by diarrheal deaths) parameters. Kallidaikurichi & Rao [2009] updated this index and created the IDWA-2 by changing the access from all-improved water sources to only households with piped connections. The authors argued that the revised access parameter accounted for the opportunity costs of time lost collecting water [Kallidaikurichi & Rao, 2009].

2.2.1.3 Water Vulnerability. Vulnerability is broadly defined as '*the ability or inability of individuals and social groupings to respond to, in the sense of cope with, recover from or adapt to, any external stress placed on their livelihoods and well-being*' [Kelly & Adger, 2000, p. 328]. External stresses on water systems include natural hazards such as floods, droughts, and storm surges as well as runoff changes from climate change [Gain et al., 2012].

Raskin et al. [1997] developed the water resources vulnerability index (WRVI), which is based on water supply and storage parameters, a withdrawal to discharge ratio, and a coping capacity index reflecting the nominal GDP per capita. The WRVI has two variations: WRVI-1 is a composite value of the index components while WRVI-2 is equal to the worst value for any one of the components. Because the components are weighted equally, only WRVI-1, henceforth referred to as WRVI, is considered in the rest of this paper. The composite water vulnerability index, developed by Paladini [2012], has four components: industrial growth rate, level of development, water stress, and water availability. GDP per capita, domestic and industrial water use, electricity production, HDI, and population density are some of the parameters included in this index [Paladini, 2012].

2.2.1.4 Water Security. Lautze & Manthrithilake [2012] developed a water security index for 46 countries in Asia that includes five components: basic household needs, food production, environmental flows, risk management, and water independence. They concluded that the water security index strongly correlated with the economic development of the 46 nations they studied. The Asian Development Bank's (ADB) national water security index also has five components: household water security, urban water security, environmental water security, economic water security, and resilience to water-related disasters [ADB, 2013a]. Despite the inclusiveness of this framework, water security indices rarely account for seasonal water-related shocks.

2.2.2 Parameter and Component Descriptions

A comprehensive list of parameters comprising the indices listed above was compiled. Following Lawrence et al. [2002], the parameters were organized into five components: resources, access, use, capacity, and environment. Where appropriate, the results and tables are organized using these component classifications. The resource component represents the amount of water physically available to a region. The access component represents accessibility to improved water and sanitation resources within one kilometer (km). Improved water sources include household connections, public standpipes, boreholes, protected dug wells, protected springs, and rainwater collection; improved sanitation facilities include connection to a public sewer, septic system, pour-flush latrine, simple pit latrine, and a ventilated improved pit latrine [WHO & UNICEF, 2012].

The water use component represents the amount of water used in the nation, either in sum or partitioned across different sectors (e.g. agricultural, domestic, and industrial). 'Water use' can refer to either water withdrawal or water consumption; a portion of withdrawn water is returned to a water source, while consumed water is lost to mechanisms such as evaporation and is thus no longer available to meet human or environmental needs. The capacity component is divided into two sub-components: soft capacity and hard capacity. Soft capacity refers to non-engineered solutions to water management such as education and institutional capacity, while hard capacity refers to built infrastructure such as dams and wastewater treatment plants [Gleick, 2003; Brown & Lall, 2006]. The environment component represents the interactions between the water resources and the ecosystem, which plays a significant role in protecting the quality and quantity of water.

2.2.3 Overview of Analysis

The water indices for Bangladesh and Sri Lanka were compared to determine the relative rankings of these countries. The Falkenmark indicator and the social water scarcity index for Bangladesh and Sri Lanka were calculated based on the most recent Food and Agriculture Organization (FAO) and UN Development Programme (UNDP) data [FAO, 2013; UNDP, 2013a]. The remaining indices were compiled from original publications. Although the data used to develop indices are from different years, it is assumed that the relative placement of Bangladesh and Sri Lanka has not changed over time.

After compiling a comprehensive list of parameters comprising the water indices, the parameters were organized into the five components. When possible, the most recent parameter values were obtained from the FAO and other resources. Otherwise, original publication data were used.

Drawing on knowledge about human-water interactions in Bangladesh and Sri Lanka, the exploration identified missing parameters as well as inconsistencies in the quantification of included parameters within each of these components. Information is noted when there is no readily available information for missing parameters.

2.3. Results

2.3.1 Indices

Water indices for Bangladesh and Sri Lanka have been shaded in Table 2.1 to indicate the country with a more favorable ranking. Bangladesh has more physical water resources than Sri Lanka at the national level (i.e., the Falkenmark indicator and social water scarcity index). Water poverty indices (i.e., the WPI, rural water livelihoods index, and the IDWA-2) suggest that Sri Lanka's political and financial resources are sufficient to compensate for its fewer physical water resources. The water vulnerability indices give a mixed message: the WRVI suggests that Sri Lanka is more stressed, while the composite water vulnerability index suggests that Sri Lanka is more resilient. Overall, however, Sri Lanka ranks more favorably in water security indices (i.e., the national water security index and the water security index) than Bangladesh.

Table 2.1. Indices for Bangladesh and Sri Lanka

Index	Bangladesh[a]	Sri Lanka[a]	Source
Falkenmark Indicator	8,153 m^3/person/year (No water stress)	2,509 m^3/person/year (No water stress)	Falkenmark, 1989; Data: FAO, 2013
Social Water Scarcity Index	2.4 (relative sufficiency)	5.6 (relative sufficiency)	Appelgren & Klohn, 1999; Data: FAO, 2013; UNDP, 2013a
Water Poverty Index	58.1 out of 100	58.5 out of 100	Lawrence, Meigh, & Sullivan, 2002
Rural Water Livelihoods Index	65.44 out of 100	68.62 out of 100	Sullivan et al., 2009
Index of Drinking Water Adequacy-2	24 out of 100	37 out of 100	Kallidaikurichi & Rao, 2009
Water Resources Vulnerability Index	3 (Stress)	4 (High stress)	Raskin et al., 1997
Composite Water Vulnerability Index	0.11 (Low resilience)	0.22 (Upper-low resilience)	Paladini, 2012
National Water Security Index	1 out of 5	2 out of 5	ADB, 2013a
Water Security Index	13.5 (Poor)	15 (Satisfactory)	Lautze & Manthrithilake, 2012

[a]*Shaded indices indicate country with a more favorable ranking*.

2.3.2 Parameter Values

Resource parameters include long-term annual water resource averages (either total or based on the source of water, that is, within or outside country borders), a measure of the inter-annual variability in precipitation, and extreme weather indicators. Although Bangladesh has more total water per capita than Sri Lanka, Sri Lanka has more internal water resources per capita than Bangladesh, due to Sri Lanka's lack of dependence on external sources (Table 2.2). As measured by the coefficient of variation in precipitation, inter-annual variability in precipitation is greater in Sri Lanka than in Bangladesh. According to the national water security index, Bangladesh is more prone than Sri Lanka to floods, windstorms, droughts, and storm surges [ADB, 2013a]. Neither the WRVI nor the composite water vulnerability index contains any parameters measuring extreme weather.

Access parameters measure the percentage of the population with access to improved water sources (either total or only as household connections) and sanitation. Some of the indices also distinguish between access parameters for urban and rural populations. Each country's urban population has greater access to water than its rural population. Bangladeshi urban and rural populations have equal access to sanitation while Sri Lanka's rural population has higher access to sanitation than the country's urban population. Sri Lanka's urban and rural populations each have greater access to improved water sources and sanitation than the corresponding Bangladeshi populations (Table 2.2).

Most of the indices in Table 2.1 include water withdrawal values, although some of the parameters are labeled generally as 'use' (Table 2.2). The indices listed in Table 2.1 quantify water withdrawals as either a volumetric measurement per capita or as a percentage of total renewable water resources; as normalized data better reflect quality of life, all the data presented in Table 2.2 have been normalized by total water resources. Some indices consider total withdrawal values while others prioritize certain sectors over others. For example, IDWA-2 prioritizes domestic use by focusing specifically on drinking water while the water security index considers only the agricultural use of water. The composite water vulnerability index includes volumetric inputs for both total withdrawals and water use by the industrial and domestic sectors, but does not consider agricultural use [Paladini, 2012]. Of the indices listed in Table 2.1, only the WPI explicitly includes a water consumption parameter that captures the percentage of a country's land that is under severe water stress (i.e. where the water consumption is greater than 40% of its available water) [Lawrence et al., 2002; YCELP & CIESIN, 2005]. A greater amount of water is being withdrawn (both per capita and as a percentage of total available water) in Sri Lanka than in Bangladesh in each of the three sectors (Table 2.2). Because most agricultural water use is consumptive [Vaux, 2012], a higher proportion of Sri Lankan land is stressed than that of Bangladeshi land [YCELP & CIESIN, 2005].

Soft capacity parameters include metrics of national education, health, income, and corruption. Education, health, and income parameters are commonly used to assess the level of a nation's development. The HDI is a composite index commonly used as a measure of a nation's soft capacity. Some of the water indices include HDI as a parameter (e.g. the social water scarcity index) while others explicitly include individual metrics for education, health, and income. The WPI, for example, uses HDI parameters for education and income, but replaces the health parameter of life expectancy with child mortality rate because the authors argue that the latter is more closely related to access to clean water (Lawrence et al., 2002). Sri Lankans are more educated than Bangladeshis, both in terms of years of schooling and literacy rates. Sri Lankans are also healthier on average, with a greater life expectancy at birth and a lower child mortality rate. Bangladesh has a lower percentage of undernourished people than Sri Lanka. Sri Lanka has higher income per capita (both GNI (gross national income)and GDP) and a higher GDP growth rate. However, Sri Lanka also has a higher GINI coefficient, indicating greater inequality in income distribution within the country. Corruption is addressed by only one index evaluated –the rural water livelihoods index (RWLI). The corruption perception parameter used in this index suggests that Sri Lanka is significantly less corrupt than Bangladesh. Overall, Sri Lanka has a higher soft capacity than Bangladesh (Table 2.2).

In the indices reviewed, hard capacity is seldom evaluated but has been operationalized as the presence of major infrastructure, such as large reservoirs and wastewater treatment plants. Both Bangladesh and Sri Lanka have approximately the same amount of large storage capacity (Table 2.2). The water security index includes a risk management parameter that measures the extent to

Table 2.2. Water Index Parameter Values for Bangladesh and Sri Lanka

	Parameters		Bangladesh[a]	Sri Lanka[a]	Source	Indices using parameters[b]
Resources	Total renewable water sources (m^3/person/year)		8,153	2,509	FAO, 2013	FI, SWSI, WPI, CWVI
	Total renewable water sources located within a nation's boundaries (m^3/person/year)		698	2,509	FAO, 2013	IDWA-2
	Dependence on external sources		91.4%	0%	FAO, 2013	WSI, WRVI
	Inter-annual variability in precipitation		0.11	0.20	Raskin et al., 1997	WRVI, RWLI[c]
	Flood Indicator		0.23	0.44	ADB, 2013a	NWSI
	Drought Indicator		0.13	0.51	ADB, 2013a	NWSI
	Coastal Indicator		0.20	0.44	ADB, 2013a	NWSI
Access	Population with access to improved water	Total	83%	93%	UN, 2013b	WPI, CWVI, WSI
		Urban	85%	99%		
		Rural	82%	92%		RWLI
	Population with household connections	Total	6%	29%	ADB, 2013b; Kallidaikurichi & Rao, 2009	NWSI, IDWA-2
		Urban	20%	67%		NWSI, IDWA-2
		Rural	0.23%	3.76%		IDWA-2
	Population with access to sanitation	Total	55%	91%	UN, 2013b	WPI, NWSI
		Urban	55%	83%		
		Rural	55%	93%		RWLI
Use	Water withdrawals (% of total water resources)	Total	2.9%	24.5%	FAO, 2013	WRVI, RWLI, CWVI
		Domestic/ Municipal	0.3%	1.5%		WPI, CWVI, IDWA-2
		Agricultural	2.6%	21.4%		WPI, WSI
		Industrial	0.1%	1.6%		WPI, CWVI
	Water Consumption (% of land area that exceeds 40% of total available water)		22.9%	32.9%	YCELP & CIESIN, 2005	WPI
Capacity – **Soft**	Education	Expected years of schooling[d]	12.7	8.1	UNDP, 2013a	SWSI, CWVI
		Mean years of schooling[d]	4.8	9.3	UNDP, 2013a	SWSI, CWVI
		Literacy rate (% of adults over 15)	56.8%	91.2%	ADB, 2013b	NWSI
	Health	Life expectancy at birth (years)[d]	69.2	75.1	UNDP, 2013a	SWSI, CWVI
		Child mortality (under 5 years) (per 1000 births)	59	12	ADB, 2013b	WPI
		Percentage of undernourished people	17	24	ADB, 2013b	RWLI
	Income: GNI per capita	GNI per capita, PPP (2013 $ International)[d]	2,070	6,120	World Bank, 2013b	SWSI, CWVI
		GDP per capita at purchasing power parity ($US 2012)	1,917	6,247	ADB, 2013b	WPI, IDWA-2, WRVI, CWVI
		Growth rates of real GDP per capita (%)	4.9	5.7	ADB, 2013b	CWVI

		Parameters		Bangladesh[a]	Sri Lanka[a]	Source	Indices using parameters[b]
			GINI coefficients of income distribution	0.321	0.364	ADB, 2013b	WPI
		Corruption Index		144 of 176	40 of 176	Transparency International, 2013	RWLI
	Hard	Storage in large dams (m^3/capita)		43.2	298.0	Raskin et al., 1997; FAO, 2013	WSI, WRVI
		Wastewater treatment		17%	32%	ADB, 2013a	NWSI
Environment		Environmental flows (water available for environmental purposes)		Very Good	Poor	Lautze & Manthrithilake, 2012	WSI
		Diarrheal disease (diarrheal incidence per 100,000 people; diarrheal deaths)		1,510	21	ADB, 2013b	NWSI, IDWA-2
		Agricultural water pollution indicators	Dissolved oxygen (mg/L)	7.70	8.13	YCELP & CIESIN, 2005	WPI
			Electrical conductivity (μS/cm)	231.60	722.22		
			Phosphorus (mg/L)	0.29	0.2		
			Total suspended solids (mg/L)	4.08	Not Available		
			Fertilizer consumption per hectare of arable land (kg)	168	262		
			Pesticide consumption per hectare of arable land (kg)	0.40	0.90		
		Industrial water pollution (biochemical oxygen demand) (kg/day)		273,082	88,943	Paladini, 2012	CWVI
		River Health Indicator		0.16	0.20	ADB, 2013a	NWSI
		Biodiversity		0.54	0.66	YCELP & CIESIN, 2005	WPI

[a]Shaded values indicate country with a more favorable ranking.
[b]FI: Falkenmark Indicator, SWSI: Social Water Scarcity Index, WPI: Water Poverty Index, RWLI: Rural Water Livelihoods Index, IDWA-2: Index of Drinking Water Adequacy-2, NWSI: National Water Security Index, WSI: Water Security Index, WRVI: Water Resources Vulnerability Index, and CWVI: Composite Water Vulnerability Index.
[c]RWLI uses inter-annual variation in cattle holdings and cereal production as a proxy for the coefficient of variation in precipitation.
[d]Some indices use the Human Development Index, which is composite of these parameters. HDI represents three dimensions of human development: a long life, as measured by life expectancy at birth; access to knowledge, as measured by mean years of adult education; and standard of living, as measured by gross national income per capita, expressed in a constant purchasing power parity, PPP (2012$). The current HDI for Bangladesh and Sri Lanka are 0.515 and 0.715 respectively (UNDP, 2013a).

which countries are buffered from rainfall variability (as measured by the coefficient of variation of precipitation) through large dam storage (Lautze & Manthrithilake, 2012); nations with higher inter- and intra-annual variability in rainfall require more infrastructure than nations with little variability in rainfall. Because Sri Lanka's higher inter-annual variability is balanced by its greater upstream storage capacity (Table 2.2), both Bangladesh and Sri Lanka received the same value for the risk management parameter in the water security index (Lautze & Manthrithilake, 2012). In addition, Sri Lanka currently treats more of its wastewater than Bangladesh (ADB, 2013a).

Ecosystems are extremely complex and are not often addressed in water indices. When ecosystems are considered, they are often assessed using proxies such as environmental flows and land cover. The indices reviewed include few consistent parameters that address the environment. Parameters grouped under the environment component are either water-specific or general measures of ecosystem health. Environmental flows, or the amount of water unclaimed for human use and thus available to ecosystems, are greater in Bangladesh than in Sri Lanka (Table 2.2). Water quality impacts are measured with either human health or chemical pollution indicators. A common human health indicator is the prevalence of 'waterborne' diarrheal diseases; Bangladesh has more diarrheal incidents per 100,000 people than Sri Lanka (ADB, 2013b). Chemical pollution indicators are either agriculture-specific (i.e. the WPI) or industry-specific (i.e. the composite water vulnerability index). Sri Lanka consumes more fertilizers and pesticides per hectare of arable land than does Bangladesh. Biochemical oxygen demand (BOD), a metric related to dissolved oxygen, reflects the amount of dissolved oxygen needed by aerobic organisms to break down organic material in water (Penn et al., 2006); Bangladesh has a much higher industrial BOD than Sri Lanka (Paladini, 2012).

Biodiversity and a composite river health indicator are two general measures of ecosystem health included in the WPI and the national water security index, respectively. Biodiversity is measured as the percentage of threatened mammals and birds in the country; biodiversity is greater in Sri Lanka than in Bangladesh (Lawrence et al., 2002; YCELP & CIESIN, 2005). The river health indicator values in the national water security index were developed using GIS (geographic information system) tools to measure pressures and threats to river systems from watershed disturbance and pollution activities (such as livestock density), and the vulnerability of the river systems to alterations in natural flows from infrastructure development and biological factors (such as river network fragmentation and non-native species) (ADB, 2013a). Although information regarding soil salinization and non-native species was not provided, the Asian Development Bank reports that both countries' rivers are in very poor health, with Sri Lanka's rivers being marginally healthier than Bangladesh's rivers (ADB, 2013a).

2.3.3 Missing Parameters

During the analysis, numerous missing parameters that could contribute to a comprehensive understanding of the human-water systems of Bangladesh and Sri Lanka were identified (Table 2.3). Parameters for total, internal, and external water resources are based on long-term annual averages, which may mask seasonal variations in water availability [Brown & Lall, 2006; Rijsberman, 2006]. Due to their monsoonal climate, Bangladesh and Sri Lanka both experience high intra-annual variability in rainfall [Brown & Lall, 2006], which is not accounted for in any of the indices listed in Table 2.1. Additionally, none of the indices contains any information regarding the distribution of water resources among surface and groundwater resources. The distinction between surface and groundwater sources in quantifying water resources is critical since the two resources have significantly different recharge rates [Hornberger et al., 1998]. Sri Lanka has more groundwater per capita than Bangladesh [FAO, 2013]. While groundwater usage information is available for Bangladesh, no such information for Sri Lanka is available (Table 2.3). Villholth & Rajasooriyar [2010] report that approximately 60% of Sri Lanka's total population is currently dependent on groundwater for domestic use.

Although the indices presented in Table 2.1 include valuable access information (such as distinctions between urban and rural populations), parameters of other intra-group differences are excluded, notably between men and women. Women have been shown to be disproportionally affected by lack of water access because they are predominantly responsible for household water collection, especially in poor households [UNDP, 2006; Sultana, 2007; Sullivan et al., 2009]. Men and women fare more equally in Sri Lanka than in Bangladesh (Table 2.3: gender inequality index values closer to zero indicate that men and women fare equally).

Table 2.3. Missing Parameters

		Parameters	Bangladesh[a]	Sri Lanka[a]	Source
Resources		Groundwater resources (m^3/person/year)	140	371	FAO, 2013
Resources		Intra-annual variability in precipitation	High	Low-medium	WRI, 2013
Access		Gender inequality index	0.508	0.402	UNDP, 2013b
Use		Groundwater withdrawal (% of total resources)	79.4%	Not Available	FAO, 2013
Use		Water consumption (% of groundwater resources)	Not Available	Not Available	
Capacity	Soft	Voice and accountability (percentile rank)	34.1	29.9	World Bank, 2013a
Capacity	Soft	Political stability (percentile rank)	9.0	22.7	World Bank, 2013a
Capacity	Soft	Government effectiveness (percentile rank)	22.5	45.9	World Bank, 2013a
Capacity	Soft	Regulatory quality (percentile rank)	19.6	48.3	World Bank, 2013a
Capacity	Soft	Rule of laws (percentile rank)	19.4	52.1	World Bank, 2013a
Capacity	Hard	Small-scale irrigation schemes (% of surface water coverage)[b]	16%	25%	Mawilmada et al., 2010; FAO, 2012
Environment		Toxic metal pollution	Not Available	Not Available	
Environment		Fecal coliforms	Not Available	Not Available	
Environment		Percentage of coastal resources affected by salinization	Not Available	Not Available	
Environment		Percentage of natural vegetation land cover	11.1%	28.8%	ADB, 2013c
Environment		Deforestation rate	0.18%	0.78%	ADB, 2013b

[a]*Shaded values indicate country with a more favorable ranking.*
[b]*Due to lack of data, surface area instead of volume of water stored in small-scale irrigation schemes is listed.*

Kaufmann [2005] identifies six key aspects of governance: voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption. Of these parameters, only corruption has been included in one of the index calculations. According to the World Bank's 2012 Worldwide Governance Indicators, Sri Lanka's government is more stable and effective, and has a greater ability to formulate and implement sound policies than

Bangladesh's government, but the latter's population ranks higher for voice and accountability [World Bank, 2013a].

Dams are not the only built infrastructure present in Bangladesh and Sri Lanka. Both reservoirs and tanks play a large role in stabilizing food production in Sri Lanka (Table 2A.1). Tanks cover almost 25% of the total surface water storage area in Sri Lanka [Mawilmada et al., 2010]. Similarly, small-scale surface irrigation schemes account for 16% of national irrigation coverage in Bangladesh [FAO, 2012].

While nutrient pollution is relevant for both countries, none of the indices includes metrics for water quality issues of significant concern in Bangladesh and Sri Lanka, such as toxic metal pollution, fecal coliforms, and salinization. Additionally, although deforestation (including the conversion of forests to agricultural land) continues to threaten Asia, no information on forest cover or the amount of protected land has been incorporated into any of the indices. Currently, a higher percentage of Sri Lanka's land is covered by forests, and more Sri Lankan land is protected than is Bangladeshi land [ADB, 2013c; WRI,2013]. Annual deforestation rates, however, are higher in Sri Lanka than in Bangladesh [ADB, 2013b].

2.4 Discussion

While water indices can facilitate program evaluation and serve as tools for water managers, as stated in Section 2.1, the findings from water indices can be ambiguous. Unlike parameter level comparisons, index level comparisons offer limited insight on small geographic scales. Our parameter level analysis has shown specific metrics (e.g. education and income) that contribute to Sri Lanka's improved indices. Water index parameters, however, have limitations as outlined below.

The most notable issue uncovered during the analysis was the absence of key parameters that could greatly impact overall water indices (Table 2.3). While no single index can capture all of the complex interactions implicit in human-water systems, the omission or inclusion of key parameters can alter the conclusions drawn from an index [Grey & Sadoff, 2007]. For example, parts of both Bangladesh's and Sri Lanka's populations rely predominantly on groundwater resources, which has resulted in aquifer depletion in both countries [Senaratne, 1996; Shah et al., 2003; Brown & Lall, 2006; ADB, 2013a]. Furthermore, declining groundwater levels in Bangladesh are affecting water quality, causing adverse effects on soils, and limiting crop growth [FAO, 2012]. However, groundwater resource or usage data for both countries are glaringly absent from all the evaluated indices. This absence is in part due to a lack of available information, so policy makers and water managers should ensure that groundwater resource and usage data are being collected to help develop a comprehensive understanding of the current state of their water resources.

Similarly absent from the indices is water-specific information regarding capacity and water quality parameters. It should be noted that while general governance information is valuable, it gives little insight into the specific structure and management of water infrastructure. The general World Bank Governance Indicator for government effectiveness, for example, does not seem to adequately represent the concerns arising from limited coordination between Sri Lanka's water agencies. Education metrics (e.g. literacy rate) also provide little information regarding awareness of basic hydrological concepts such as the water cycle and how to limit contamination of water supplies. Future research should assess how information on water-specific governance and education can be collected and measured. While not a comprehensive list, Table 2.3 lists additional parameters that should be evaluated for inclusion in water indices. Until these data become available, the rationale for using certain proxies should be explicitly stated in analyses.

Few of the evaluated indices consider the complex relationships between the components. The water security index is one of the few indices to include a risk management parameter to measure the extent to which a nation is buffered from rainfall variability through large dam storage. Similarly, the presence of water agreements with neighboring countries suggests that a country's external water resources should not be ignored. Most of the evaluated indices, however, give equal weight to the parameters listed in Table 2.2, rather than examining these complex relationships when developing indices. Since the indices typically have more parameters reflecting social conditions than physical conditions, Sri Lanka has more favorable water indices despite having a third of Bangladesh's total water resources available per capita (Tables 2.1 and 2.2). Equal weighting of all parameters also causes valuable information to be lost. For example, in addition to having greater income per capita, Sri Lanka also has higher income inequality (as indicated by the GINI coefficient and the percentage of undernourished people) than Bangladesh.

The indices evaluated did not always reflect the framework implied in their nomenclature. For example, the WRVI has no parameters measuring natural hazards but the national water security index does. In addition, the WPI includes parameters measuring agricultural water quality, which are not present in any of the other indices. Inconsistencies in parameter units are also present. For example, some of the indices use only per capita volumetric measurements, whereas the percentage of water used relative to total water resources is a better indicator of the stress on a nation's water resources. Some indices also have issues with double counting: the composite water vulnerability index, for example, has a parameter representing total water use as well as additional parameters for water use by the industrial and domestic sectors [Paladini, 2012].

2.5 Conclusion

This analysis demonstrates that policy makers, water managers, and academics should use water indices with caution. Human-water systems are extremely complex, and not all of their parameters can been compassed by any one index. Therefore, researchers and water managers should be cautious when selecting and applying an index to monitor progress towards their national goals. Particular attention should be given to the selection of parameters relevant to national priorities. When possible, parameters that reflect complex hydrological characteristics and contain water-specific metrics should be used. Regardless of the shortcomings outlined here, water indices are a valuable method to integrate physical and social factors influencing human-water systems. Following these recommendations will improve the likelihood of these indices providing a comprehensive representation of the most critical aspects of a nation's water resource issues.

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Appendix: Country Descriptions

Bangladesh

Bangladesh, a least developed country, is one of the most densely populated countries in the world [UNCTAD, 2011; FAO, 2012]. Bangladesh is a riverine country with 7% of the country's total land area covered by rivers, notably the Ganges, Brahmaputra, and Meghna [FAO, 2012]. More than 90% of Bangladesh's surface water originates in other countries [Chowdhury, 2010]. The majority of rain falls during the annual monsoon, from June to

Table 2A.1 Bangladesh and Sri Lanka Country Profiles

	Bangladesh	Sri Lanka	Source
Land area (km^2)	144,000	25,332	FAO, 2012
Population (x1000)	150,494	21,025	FAO, 2013
Population density (inhabitants/km^2)	1,045	321	FAO, 2013
Population growth rate (%)	1.3	0.7	ADB, 2013b
Mean annual temperature (°C)	25°C	27°C in the lowlands, 15°C in the central highlands	FAO, 2012
Total cultivable land area (hectares per capita)	0.06	0.10	FAO, 2013
Gross domestic product, PPP ($US 2012 per capita)	1,943	6,040	ADB, 2013b

September, when 80% of the annual precipitation occurs [Chowdhury, 2010]. The country receives an annual average of 2,320 millimeters (mm) of rain but there is significant spatial variation in the amount of rainfall received, with an annual average of 1,110 mm of rainfall in the west and over 5,000 mm in the north-east [FAO, 2012; 2013]. Water is the primary transportation medium, and water-intensive industries such as agriculture, fisheries, forestry, and aquaculture are significant contributors to Bangladesh's economy.

Currently, groundwater is the primary water source in Bangladesh, comprising 79% of total water use in 2008 [FAO, 2012]. The agricultural sector, particularly paddy cultivation, is the biggest water user, accounting for 88% of the country's total water withdrawals in 2008 [Chowdhury, 2010; FAO, 2013].

Bangladesh is extremely vulnerable to frequent floods, cyclones, droughts, and storm surges. Due to its flat and low-lying topography, sea level rise is also of concern [Chowdhury, 2010]. Although the country has plentiful water during the monsoon season, there is insufficient storage throughout the country to meet the needs of people and agriculture during the dry season [FAO, 2012]. Furthermore, water quality has been adversely impacted by agricultural run-off, fecal contamination due to inadequate sanitation, saltwater intrusion, and pollution from industrial sources. To address contamination of surface water, in the 1970s, the Bangladesh government initiated a nationwide program to provide shallow groundwater tube wells to many rural residents. This provided a dependable alternative drinking water supply until arsenic contamination was discovered in 1994 [Biswas & Adank, 2004]. Today, an estimated 1 million tube wells are contaminated with arsenic, exposing over 30 million people to its toxic effects [Chowdhury, 2010; FAO, 2013]. Increased salinity in surface water has occurred because of decreased flows, and saltwater intrusion in the coastal areas is evident in groundwater drinking wells [Chowdhury, 2010; FAO, 2013].

The Ministry of Water Resources (MoWR) is responsible for the planning, implementation and operation of all water resource activities in Bangladesh. Two of the major institutions under MoWR are the Bangladesh Water Development Board (BWDB) and the Water Resources Planning Organization (WARPO). WARPO has national and regional water planning responsibilities, and the BWDB is charged with the execution of over 400 water projects. The National Water Resources Council (NWRC) is the national body responsible for water policy in Bangladesh. WARPO has a mandate to coordinate with all relevant ministries through the NWRC [Chowdhury, 2010]. Delivery of water and sewerage services in the larger cities is the responsibility of the water and sanitation authorities, whereas local governments implement water supply projects in the smaller municipalities. The Department of Public Health Engineering (DPHE) is the national agency responsible for water and sanitation facilities in the rural areas [Chowdhury, 2010]. Non-governmental organizations are primarily responsible for implementing or extending water services in the country, either directly or indirectly through micro-finance assistance [Biswas & Adank, 2004]. Bangladesh reached an agreement with India regarding equitable use of the Ganges in 1996, but no such agreements have been made for the other trans-border rivers [FAO, 2012]. Water rights in the country are linked to land ownership rights, but over 45% of the rural population in the country is either landless or 'functionally landless', owning less than 200 square meters of land [World Bank, 2013].

Sri Lanka

Sri Lanka, an island nation, is divided into three climatic zones determined by rainfall patterns: the wet zone, the intermediate zone, and the dry zone. Sri Lanka receives rain from two monsoons, the north-east monsoon and the south-west monsoon. The wet zone receives rain during both the north-east and south-west monsoon, while the dry zone, which covers three-quarters of the island, receives rain only during the north-east monsoon.

As in Bangladesh, there is high spatial variation in the rainfall patterns, with an average annual rainfall of less than 1,000 mm in the north-west and over 5,000 mm in the central highlands of the country [Gunatilaka, 2008]. Both floods and drought are issues of particular concern in parts of the island [FAO, 2012]. Because Sri Lanka is an island nation, it has no trans-border water resources. Water quality issues include agricultural pollution, fecal contamination, and saltwater intrusion, notably in the coastal areas [Villholth & Rajasooriyar, 2010].

As in Bangladesh, agriculture (predominantly paddy cultivation) plays a large role in the local Sri Lankan economy. In Sri Lanka, irrigation schemes are classified as minor, medium, and major depending on the size of the area that can be irrigated by the scheme. Small artificial lakes and ponds, known locally as tanks, dominate the minor irrigation systems [Marambe et al., 2012]. Due to overcrowding in other parts of the country, the Sri Lankan government initiated the Mahaweli Development Programme in the 1970s, which oversees the construction of medium and major irrigation systems in the dry zone.

There are approximately 40 institutions and 40 legislative acts related to water in Sri Lanka [Manthrithilake& Liyanagama, 2012]. Small-scale irrigation schemes are under the purview of the Department of Agrarian Development and are primarily managed by the farmers themselves. Medium and large irrigation schemes in the dry zone are managed collaboratively by the Mahaweli Authority of Sri Lanka and the Irrigation Department with priorities given to drinking and irrigation water over electricity generation [Manthrithilake & Liyanagama, 2012]. Unlike the set-up in Bangladesh, there is little coordination in managing general water resources in the country; for example, the Meteorological Department and the Irrigation Department both collect rainfall data but neither shares their data with the other agency [FAO, 2012; Thuraisingham, 2013]. Overlap, gaps, and conflicting jurisdictions arise from Sri Lankan water laws being administered at the agency level rather than being coordinated under a single ministry [FAO, 2012]. Water rights in Sri Lanka are linked to land ownership, so landowners have full authority over the use of surface water and groundwater resources accessible on their land [FAO, 2012]. Nevertheless, land fragmentation, landlessness, and encroachment in Sri Lanka generate inequality in access to water rights [Azmi, 2007]. To date, no comprehensive groundwater management or planning systems have been implemented in the country [FAO, 2012].

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CHAPTER 3

Drinking Water Insecurity: Water Quality and Access in Coastal South-Western Bangladesh

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ABSTRACT

National drinking water assessments for Bangladesh do not reflect local variability, or temporal differences. This paper reports on the findings of an interdisciplinary investigation of drinking water insecurity in a rural coastal south-western Bangladesh. Drinking water quality is assessed by comparison of locally measured concentrations to national levels and water quality criteria; resident's access to potable water and their perceptions are based on local social surveys. Residents in the study area use groundwater far less than the national average; salinity and local rainwater scarcity necessitates the use of multiple water sources throughout the year. Groundwater concentrations of arsenic and SpC were greater than surface water (pond) concentrations; there was no statistically significant seasonal difference in mean concentrations in groundwater, but there was for ponds, with arsenic higher in the dry season. Average arsenic concentrations in local water drinking were 2 to 4 times times the national average. All of the local groundwater samples exceeded the Bangladesh guidance for SpC, although the majority of residents surveyed did not perceive their water as having a "bad" or "salty" taste.

3.1 Introduction

Water is essential to life and human health, economic development, food security, poverty reduction, and sustainable ecological functions [UN Water, 2013]. Given that the world's population is expected to reach eight billion by 2025, growing demands on drinking water supplies and water for food production are evident, and competing uses of limited resources are inevitable [UNDP, 2006]. Anticipated anthropogenic climate change impacts of higher temperatures, drought, more erratic precipitation patterns, and more intense storms are expected to intensify water demands [IPCC, 2007]. There are myriad terms that describe human social and environmental relationships with water. One of the most comprehensive terms currently being used is "water security", which UN Water defines as:

> *The capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability. [UN Water, 2013, p.1].*

Many drinking water assessments for Bangladesh have focused at the national level that does not reflect local variability, nor illustrates temporal differences due to the seasonality of water supplies. The objective of this paper is to report on the findings of an interdisciplinary investigation of the state of drinking water security in a small area of coastal south-western Bangladesh to illustrate the importance of scale in assessing water security. The assessment of local water security is focused on water quality and the issues that affect access to potable water. The types of local water sources and uses are described, and spatial and temporal trends in local water quality are identified. Drinking water quality is assessed by comparison of locally measured concentrations to national concentrations and to water quality criteria, and resident's access to potable water are described based on local social surveys.

3.1.1 Factors affecting water security in Bangladesh

The coastal region of Bangladesh is predominantly rural, relying on rice paddy farming, fishing, and aquaculture for its primary livelihoods [Chowdhury, 2010; FAO, 2009]. Shrimp farming has intensified over the past two decades, greatly changing the local landscape, and negatively affecting surface and groundwater resources [Datta et al., 2010].

Throughout Bangladesh ineffective water management, insufficient governance, and the lack of infrastructure greatly affects water security, and drinking water needs compete with irrigation demands. Agriculture employs about two-thirds of the country's population, and rice cultivation is the most important activity, requiring vast amounts of surface water and groundwater for irrigation [Chowdhury, 2010; Abedin et al., 2014]. Food security for the nation is thus heavily water-dependent [Falkenmark, et al. 2009; UNESCO, 2012].

Drinking water sources in rural are varied, and include shallow groundwater obtained through tubewells, small ponds with and without pond sand filters (PSF, a sand and gravel filter), harvested rainwater, bottled water, and river water. Rainwater collection devices are of generally small volume (insufficient to last the entire year), and municipal reservoirs are essentially non-existent. This lack of adequate water storage infrastructure intensifies water insecurity [Ansari et al., 2011].

Bangladesh is vulnerable to water insecurity partially because of its environmental circumstances. Being a low-lying deltaic country of exceptionally dense population, Bangladesh is susceptible to a variety of environmental stresses and natural disasters; these stresses can exacerbate the difficulties accessing potable water [FAO, 2009; Chowdhury, 2010; Abedin, et al. 2014]. For example, south-west Bangladesh was severely impacted by cyclone Aila in 2009; many drinking water sources were inundated with saline tidal water and became unusable [FAO, 2009; Mallick, et al. 2011].

Although the country has immense natural water resources, drinking water quantity and quality are greatly affected by Bangladesh's monsoonal climate. Rainfall in Bangladesh is not consistent temporally or spatially; 80% of the rainfall occurs during June to September [Chowdhury, 2010; Abedin et al., 2014]. This seasonal nature of water supply affects the choices people make in selecting drinking sources and the quality of those sources. The long dry season results in local water scarcity and degraded water quality, and necessitates the use of multiple drinking water sources to meet basic personal needs [Ansari et al., 2011]. In the dry season, rainwater is not available for drinking, and surface water sources become stagnant.

Groundwater is used extensively for drinking water throughout Bangladesh. On the coast, most of the groundwater used for water supply is pumped from the top 150 meters, but much of it is saline [Chowdhury, 2010; Ravenscroft, 2003]. Aquifers would be expected to be flushed and recharged seasonally during the monsoon, bringing an abundance of fresh subsurface water, but recharge is highly variable due to the presence of intermittent, thick deposits of clays [Ravenscroft, 2003]. Over one million community tubewells and 10 million private tubewells are in use in Bangladesh [BBS, 2012]. It has been estimated that 15 to 100 people are served by one tube well [WASSA, 2004; BBS, 2011].

In Bangladesh, the main issues surrounding water quality are microbial pathogens, arsenic (As) in groundwater, and salinity. Although a significant issue, bacterial contamination of water is not addressed here. For decades, the widespread contamination of groundwater by As in Bangladesh has been recognized as a severe problem [Ahmed et al., 2006; Ahmed, 2011].

Although it is naturally-occurring, As contamination is a continuing public health issue in Bangladesh, potentially affecting millions of people [Chowdhury, 2010; BBS, 2011]. Salinity has been recognized as a significant water problem in coastal Bangladesh for some time, as a result of both man-made and natural causes [Uddin, 2003; Rahman & Bhattacharya, 2006; Mahmuduzzaman et al., 2014]. While water quality in Bangladesh has been acknowledged as a problem, many studies focus on either arsenic *or* salinity, not both. What has not readily been recognized, however, is drinking water that contains arsenic also contains numerous other toxic chemicals, so the risk to residents is vastly under reported because risks are considered cumulative [USEPA, 2007; WHO, 2011].

3.1.2 Impacts of water insecurity

The effects on human health from poor water quality are well-known [WHO & UNICEF, 2011]. Chronic exposure to high levels of arsenic is associated with a multitude of health issues including cancers, cardiovascular disease, and skin lesions [Joseph et al., 2015]. The health effects of dietary salt intakes are understood and well-documented. However, studies on health effects of drinking saline water are scarce. Khan et al. [2011; 2014] demonstrated significant risk of pre/eclampsia and gestational hypertension in women in the Dacope upazila of Bangladesh; rates were higher in coastal residents compared to non-coastal areas. Khan also showed that women consuming tubewell drinking water were at higher health risks than those who used pond water or rainwater [Khan et al., 2014]. Health impacts were also found to be considerably higher in the dry season than in the monsoon season [Khan, 2008].

Not only are there adverse health effects to people from drinking contaminated water, but there are lost opportunity costs associated with the time in collecting water, and time spent away from education and occupational pursuits; all of these are considered to affect both an individual's and a community's development potential [UNDP, 2006]. In Bangladesh, as in many developing countries, women carry the burden of water collection. Internationally, it has been estimated that 64% of water collection duties fall to women [WHO & UNICEF, 2011].

3.1.3 Assessment of water security on a national basis

Bangladesh was issued a Millennium Development Goal [MDG] in 2000 to halve the proportion of people in the country that do not have access to safe drinking water by 2015 [UN, 2000]. There was no specific quality requirement; water was considered "safe" if obtained from an "improved water source" [tubewells are considered "improved", but ponds are not] [WHO & UNICEF, 2000; 2011]. Taking arsenic contamination of groundwater into consideration, it was estimated in 2015 that 86% of Bangladesh's population is considered to have access to safe drinking water, well towards its goal of 89% [GOB, 2015; BBS, 2011]. However, this method of estimating access to "safe" water is flawed because it does not address the quality of drinking water; access issues such as seasonal availability, the number of sources used, and time it takes to collect water; or the reliability of the sources.

In Bangladesh, the population that continues to be without safe water is the country's poorest and most vulnerable. Support documentation for the MDG defines distance to an "improved source" as within one kilometre (1 km) of the dwelling. Although the MDG does not account for the time needed to collect water, for accounting purposes, the time taken for water collection is usually assumed to be 30 minutes or less, round trip [UNESCO, 2009]. The success of a rural water supply is directly related to the ability to keep it in working order, which is related to who owns the source, where it is located, its acceptance by the community, and local leadership [Crow & Sultana, 2002; WHO & UNICEF, 2011].

All of the factors described that contribute to water security at the national level also affect water security at the local level. The complexity and variability of these factors suggest that water security assessed at a national level could miss significant differences, and might be better assessed at the local scale, as described in this study.

3.1.4 Study Area

The study area is "Polder 32" (P32), located in the Khulna district, Dacope upazila in southwest Bangladesh, 60 km north of the Bay of Bengal. The upazila is located between 22°24' N and 22°40' N and 89°24' E and 89°35' E. This area was devastated by cyclone Aila in 2009 [Mehedi, 2010], and at the time of this study (2012), parts of the polder were still recovering. Dacope upazila has 10 unions and 716 mauzas (which are basically comparable to census blocks in the US). P32 consists of two unions: one north (Kamarkhola), which consists of two mauzas: Kamarkhola and Sreenagar/Kalinagar, and one south (Sutarkhali), which consists of four mauzas: Sutarkhali, Gunari, Nalian, Kalibogi/ Sutarkhali [BBS, 2012]. P32 is home to approximately 44,000 people is about 19 km long and 7 km wide (Table 3.1).

Table 3.1. National and Local Demographics (2011 Census)[a]

Parameter	Bangladesh	Khulna District (Zila)	Dacope Upazila	Polder 32[b]
Area (sq. km)	147,570	4,394	992	495
Population (enumerated)	144,043,697	2,318,527	152,316	43,957
Households (total)	32,173,630	547,347	36,597	11,022
Households (% rural)	77	66	91	100
Density (pop. per sq. km)	976	1,046	1,027	980[c]
Average household size	4.4	4.2	4.1	4.0
Hindus (%)	8.5	22.7	56.5	33.7
Muslim (%)	90.4	76.6	41.6	65.8
Literacy rate (%,7+ yr, both)	51.8	60.1	56.0	58.6
Ratio, Employed male to female (7+, not in school)	na	0.72	0.59	0.56
Sanitary toilet (water seal & not, %)	64	78	67	35
Electricity connection (%)	57	64	28	17
Main DW source-tap (%)	10.3	2.0	0.7	0.95
Main DW source-tubewell (%)	83.9	83.7	30.6	13.6
Main DW source-other (%)	5.8	14.3	68.7	85.4

[a]*Sources: [BBS, 2012; 2014; 2015]; na=not available.*
[b]*Polder 32 data is calculated from individual data from six comprising P32.*
[c] *Density for P32 is actually lower; density only reported by Union.*

P32 is completely surrounded by tidal rivers, and is bounded on the southern end by the Sundarbans mangrove forest, to the east by Polder 33, by the north and west by Polder 31 (Figure 3.1) [BBS, 2012]. P32 is densely populated, completely rural, and impoverished (using electricity connection ,17%, as a proxy). This rate is substantially lower than the Khulna district (64%), and the national rate (57%), but is similar to Dacope upazila. P32 has about half the rate of sanitary toilets (35%) compared to Bangladesh as a whole, Khulna district, and Dacopa upazila. P32 also has a smaller Muslim population (65.8%) compared to national statistics, but is higher than Dacope upazila (Table 3.1).

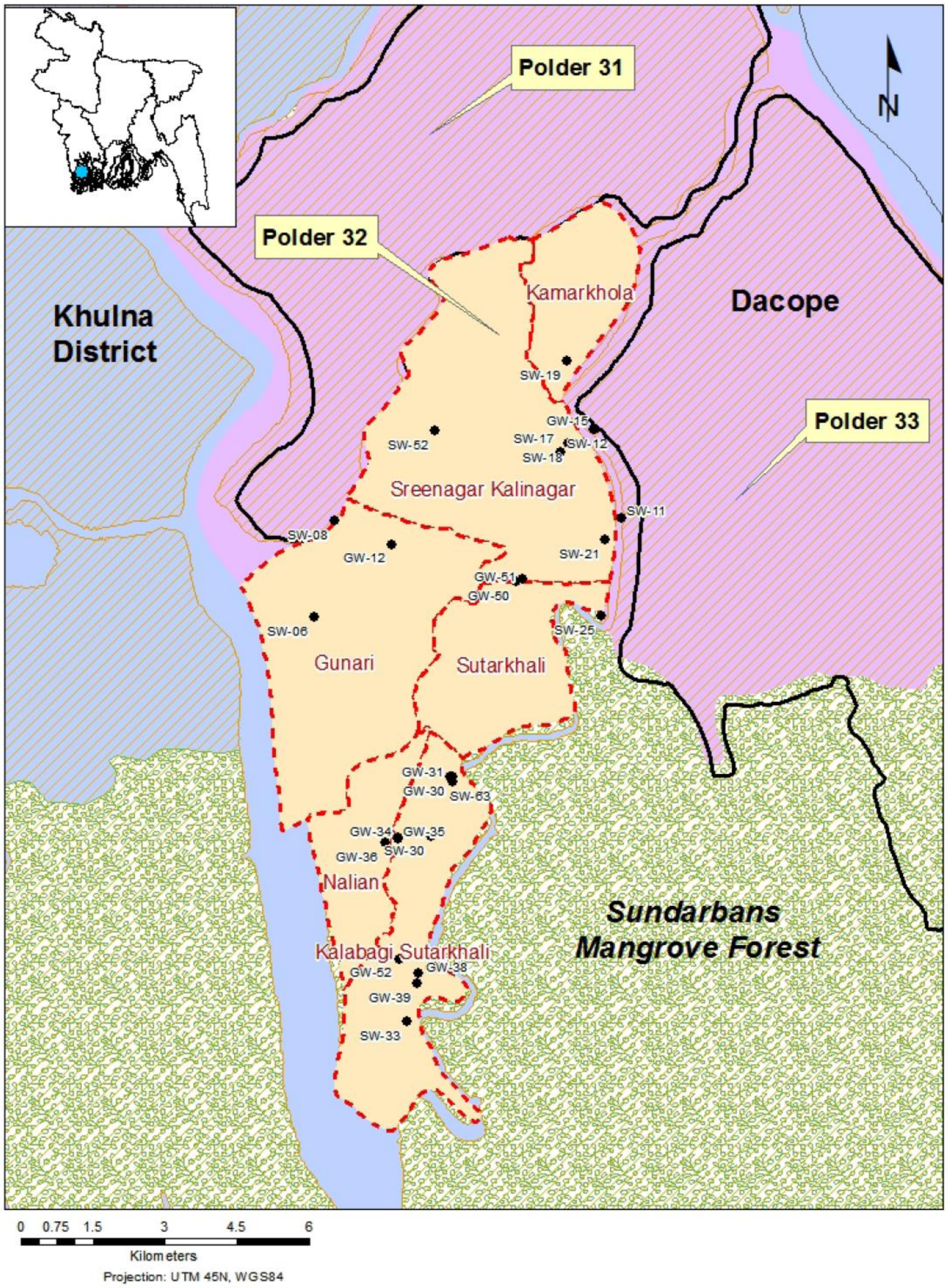

Figure 3.1. Location of Polder 32

According to the 2011 Census [BBS 2012], only 13.6% of P32 is reported to use groundwater (via tubewells) as its main drinking water source, which is very different than Bangladesh at the national level (83.9%)(Table 3.1). However, as will be described here, the Census data only gives part of the picture for rural potable water use in Bangladesh; it does not address people's need to use multiple sources during the year, nor does it identify the sources as private or community-owned.

3.2 Materials and Methods

During the local water quality investigation reported here, local residents were asked where their drinking water sources were located, and water sampling was biased towards those locations, based on field accessibility. Water samples were collected from 26 different drinking water sources: 12 groundwater (shallow tubewells) locations and 14 ponds, over two wet and dry seasons for the years 2012-2013 (Figure 3.2). Two harvested rainwater samples were also analyzed for limited parameters. In addition to P32, a few samples were collected from adjacent Polders 31 and 33. Quality assurance/quality control (QA/QC) samples were also collected and

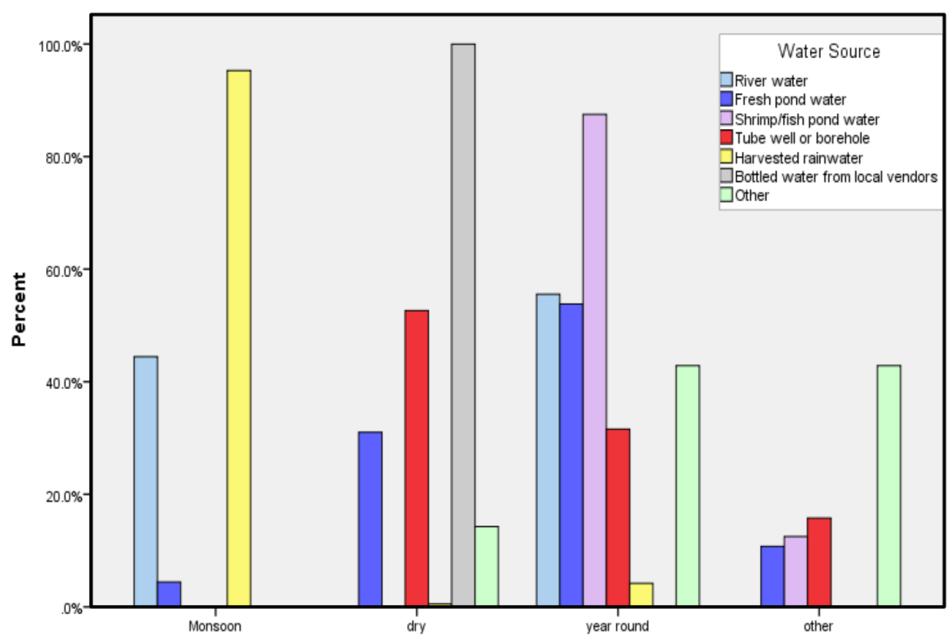

Figure 3.2. Types of Drinking Water Sources Used Seasonally (Ethnosurvey)

analyzed during the local field investigation. Field parameters were obtained with a portable Hydrolab models 4a and DS5, and locations ascertained using a Trimble GeoXT 6000. The samples were analyzed by Vanderbilt University's Civil Engineering lab for a variety of cations and anions using Inductively Coupled Plasma-Mass Spectrometry (ICP-MS), Ion Chromatography (IC), and Total Organic Carbon (TOC) analyses. A companion study to this assessment is described by Ayers et al. (2016) which presents the sampling and analytical protocols in detail, as well as all of the raw data.

The two years of water quality data were combined by season and tested for normality by use of the Shapiro Wilkes test, as well for kurtosis and skewness. Kurtosis quantifies whether the shape of the data distribution matches the normal (Gaussian) distribution, which has a kurtosis of 0. Skewness tests for symmetry of the data distribution; the degree of symmetry is an indicator of the normal distribution [Helsel & Hirsch, 2002]. Because all of the detected chemical concentrations did not fit a lognormal (or other typical distribution) and the sample size was small (<50), a nonparametric test (Wilcoxon Rank Sum test) was used to evaluate statistical significance of differences in means in drinking water sources between the wet and dry seasons.

In addition to the physical measurements, a detailed Ethnosurvey was conducted by Vanderbilt's social science team from October to December 2013 in 200 randomly selected households in the northernmost and southernmost mauzas: Kamarkhola and Kalibogi/Sutarkhali, respectively, on P32. The Ethnosurvey was designed as a pilot for a wider geographic study of the region, and provided information on local drinking water sources, uses, and access issues. An additional Informal Water Use Survey of 31 respondents was conducted during the October 2013 sampling season.

3.3 Results & Discussion

Assessment of drinking water security can be perceived in terms of*: availability*—types and numbers of sources available, source ownership, other uses, sufficient water quantity, and reliability/continuity of service based on seasonality, treatment, and maintenance; *accessibility*—available within a reasonable distance, or able to be collected within a reasonable time, affordable, and free of gender and class discrimination; and *quality*—safe for consumption and aesthetically acceptable [Wouthers, 2010; Crow & Sultana, 2002].

3.3.1 Drinking water availability & accessibility

3.3.1.1 Drinking water sources and ownership. The water quality investigation of P32 indicated that over 84% of the drinking water sources sampled were identified as "community" sources, which in this context meant that more than one family could access the source, and was responsible for its operation and upkeep. In the Ethnosurvey it was found that some types of drinking water source tended to be privately owned and maintained, while others were community owned and maintained. In both mauzas evaluated in the Ethnosurvey, the water sources were predominantly owned by the households, although there were more household-owned sources in Kamarkhola (52%) than in Kalibogi (39%). The most common water sources that were noted as owned by households in both mauzas, on average, were rainwater (70%) and fresh pond water (distinguished from shrimp ponds)(20%). The water sources most noted as community-owned were fresh ponds (49%) and river water (30%). Results indicate that P32 residents rely on surface water sources more than groundwater. By comparison, the 2011 Census [BBS, 2012] indicated that 5.8% of the population uses "other" as its main drinking water source on a national level, which includes ponds, rainwater, and surface waters (Table 3.1).

3.3.1.2 Non-Drinking Water Uses. In the Ethnosurvey of the two P32 mauzas, queries were made about which water sources were used for purposes other than drinking. The most frequent types of water sources noted for cooking were fresh pond water (57 %), and harvested rainwater (25 %). Fresh pond water (44 %), river water (29 %) and shrimp/fish pond water (20 %) were most commonly noted as sources for bathing. Water sources noted predominantly for household cleaning were fresh pond water (44%), river water (24%), and shrimp/fish pond water (24%). Other than for drinking, tubewells were noted for other uses less than 2%. These results indicate the possibility of reserving higher quality water for drinking and cooking.

3.3.1.3 Seasonality. The Informal Water Use Survey of P32 found that no household used just one water source during the year; in fact, 74% used two or more sources, 16% used three or more and 10% used four or more sources. Residents also reported in the Informal Water Use Survey that they used groundwater, rainwater, and surface water for equal months during the year on average (3.6, 4.8, and 3.7 months/year, respectively). The Ethnosurvey indicated that 48% of the residents in two mauzas in P32 use harvested rainwater, 40% use fresh pond water, and 5% use tubewells as a drinking source at some time throughout the year. The water sources used predominantly in the monsoon season for drinking were harvested rainwater (94%) and river water (44%). Sources used most frequently in the dry season only were bottled (100%), tubewells (53%), and fresh pond water (31%). The results for the sources used year-round were somewhat confusing: shrimp/fish ponds (88%), river water (56%); and fresh pond water (54%)(Figure 3.2). These results indicate that rainwater is used extensively when it is plentiful in the monsoon season, but is precluded from being used year-round, presumably from lack of storage. In addition, of the population that uses tubewells for drinking water, about 32% rely on using tubewells year-round.

3.3.1.4 Treatment and reliability. In the Ethnosurvey of the two P32 mauzas, it was found that the most common home water treatment (HWT) of surface water was “none” (51%), followed by “fitkari” (also known as alum) (24%); and pond sand filters (PSF) (18%); only 1 responded "boiled" as water treatment. Groundwater is not treated. In this area of Bangladesh people do not have enough fuel to boil their drinking water, or the wealth to buy fuel. No municipal water supply was available in P32, except for in the mauza of Nalian, which has a water treatment facility (not sampled in this investigation). Although a few “taps” and water lines were observed, these are sourced to fresh ponds, usually with a PSF.

3.3.1.5 Maintenance of drinking water sources. When asked during the Ethnosurvey about who maintained the water sources in the two mauzas evaluated, collectively more sources were maintained by households (47%), rather than community (26%), “not maintained” (17%), or NGOs (1%). When viewed by water source, those most often noted as “not maintained” were river water (62%), and shrimp/fish ponds (35%). The water sources most often maintained by the household included harvested rainwater (91%), shrimp pond water (44%), and fresh pond water (27%). People indicated that rainwater was not maintained by the community (0%), and that tubewells (52%), “other” (54%), and fresh ponds (46%) were more likely to be maintained by the community.

3.3.1.6 Water collection travel time, distance, and gender. In the P32 Ethnosurvey 81% of the respondents said that a water collection trip took 20 minutes or less (one roundtrip); this time is comparable to that established by the MDG. However, the results do not consider season, or the number of trips per day.

3.3.2 Drinking water quality

Only detected constituents with Bangladesh water quality standards [GOB, 1997] were further evaluated in this investigation: specific conductivity, aluminium (Al), arsenic (As), boron (B), barium (Ba), calcium (Ca), chloride (Cl), copper (Cu), fluorine (F), iron (Fe), potassium (K), magnesium (Mg), manganese (Mn), sodium (Na), phosphorus (P), nickel (Ni), zinc (Zn), and nitrate (NO_3^-). The conductivity of solution is a measurement of how well it can conduct an electrical current for a unit length and unit cross-section; when adjusted for ambient temperature, the measurement is referred to as "specific conductivity" (SpC). The conductivity of water is a function of the rate of movement of charges, which is a function of the speed, magnitude of the charge, and concentrations of the total individual ions in the water. The more dissolved ions in water, the greater its electrical conductivity [Kemker, 2014].

As described below, tubewell concentrations for the two constituents of primary interest (As and SpC) were greater than pond concentrations. There was no statistically significant seasonal difference in means in As and SpC found in tubewells collectively, but there was a difference for ponds. This is expected since it is thought that shallow groundwater in this region is not being diluted and recharged by rainwater, whereas fresh ponds would intercept all incident precipitation. Ayers et al. [2016] found slightly different groundwater results for the same geographic area; however, non-drinking water sources were included in that assessment.

Arsenic is usually present in natural waters at concentrations < 2 ug/l [WHO, 2011]. The range of As concentrations in tubewells found in this investigation was 2.4 to 254 ug/l in May (dry season), and 2.8 to 36.6 ug/l in October (wet season). The average concentration of As in tubewells on P32 was over 40 times natural concentrations: 93.5 ug/l in May and 82.5 ug/l in October (Table 3.2). The range of As concentrations in ponds on P32 was 3.1 to 49.1 ug/l in May, and 2.8 to 36.6 ug/l in October. Average As concentrations in ponds were much lower than tubewells: 17.4 ug/l in May and 9.78 ug/l in October. For tubewells, mean As concentrations were not statistically significantly different from May (dry season) to October (wet season). In fact, of all constituents, only Fe and NO3- were found to be significantly different by season in groundwater. However, As concentrations in ponds were significantly different by season, along with many other parameters.

The typical range of electrical conductivity for fresh rivers is 0 to 800 uS/cm (< 0.5 part per thousand, ppt), and seawater is 55,000 uS/cm (about 35 ppt). Natural fresh groundwater has electrical conductivity levels that are generally < 300 uS/cm [Kemker, 2014]. The range of SpC concentrations tubewells on P32 was 10 to 25 times higher than natural concentrations: 3,124 to 8,012 uS/cm in May (dry season), and 3,565 to 8,220 uS/cm in October (wet season). The average SpC concentration in tubewells on P32 was 5,230 uS/cm in May and 5,731 uS/cm in October (Table 3.2).

The range of SpC concentrations in ponds on P32 was 1,019 to 8,136 uS/cm in May, and 1,017 to 2,480 uS/cm in October. Average SpC concentrations in ponds were much lower than tubewells, but were lower during the wet than the dry season: 2,725 uS/cm in May and 1,589 uS/cm in October (Table 3.2). For tubewells, mean SpC concentrations were not found to be statistically significantly different from May (dry season) to October (wet season); mean SpC concentrations in ponds were found to be significantly different by season.

3.3.3 Comparisons of P32 concentrations to water quality criteria

The P32 water results were compared to the current government of Bangladesh [GOB, 1997] drinking water standards to ascertain the level of quality of local drinking water. GOB drinking water standards were more stringent than WHO guidelines (2011) for all of the chemicals evaluated except As and Cl. Arsenic was evaluated for both GOB and WHO standards and all other chemicals were evaluated for GOB standards only.

Table 3.2. Averages of Drinking Water Sources Over Dry and Wet Seasons, 2012-2013

	GOB Criterion[a] (ug/l)	Tubewells (ug/l) [b]				Ponds (ug/l) [b]			Rainwater (ug/l) [b, c]		
		Mon	**N**	**Mean**	**Std. Dev. [d]**	**N**	**Mean**	**Std. Dev. [d]**	**N**	**Mean**	**Std. Dev. [d]**
SpC [e]	2,000	5	28	5,230	1,300	20	**2,725**	1,724		na[f]	
		10	17	5,741	1,394	22	**1,589**	394	2	7.25	2.33
Al	200	5	26	25.7	11.9	20	21.8	16.0		na	
		10	13	35.4	13.3	21	22.2	9.15	1	8.17	0
As	50	5	27	93.5	72.6	18	**17.4**	13.0		na	
		10	17	82.5	71.6	22	**9.78**	8.24		na	
Ba	10	5	28	375	327	20	**77.3**	31.3		na	
		10	17	452	346	22	**37.6**	16.0	1	21.5	0
B	1,000	5	28	558	175	20	185	166		na	
		10	17	604	166	22	130	49.6		na	
Ca	75,000	5	28	99,741	48,669	20	66,517	24,715		na	
		10	17	115,887	59,826	22	50,163	20,016	2	858	489
Cl	1 x 10^6	5	28	1,370,754	547,628	20	**765,658**	665,566		na	
		10	17	1,505,697	415,813	22	**364,265**	111,634	2	2,140	410
Cu	1,000	5	28	9.76	10.1	20	47.2	182		na	
		10	12	9.51	8.96	15	3.44	1.89		na	
F	1,000	5	18	4,282	2,324	20	**2,502**	2,124.54		na	
		10	0	na	na	10	**102**	46.9		na	
Fe	650	5	28	**1,679**	2,011	18	15.8	25.8		na	
		10	17	**2,538**	1,849	11	5.71	3.97	1	10.6	0
K	12,000	5	28	30,171	9,681	20	**30,208**	18,657		na	
		10	17	24,768	6,092	22	**15,460**	5,518	2	107.0	28.9
Mg	35,000	5	28	87,933	29,239	20	**54,324**	35,022		na	
		10	17	95,105	34,167	22	**31,706**	8,150		81.0	14.0
Mn	100	5	28	130	218	20	**174**	217		na	
		10	17	110	80.9	20	**36.3**	51.0		na	
Na	200,000	5	28	939,856	366,982	20	**521,210**	459,566		na	
		10	17	991,567	244,971	22	**247,121**	78,505	2	1,411	230
Ni	0	5	22	2.62	1.56	13	1.57	1.22		na	
		10	15	4.30	2.92	13	2.57	1.46		na	
P	0	5	28	2,964	1,918	20	143	324		na	
		10	17	3,000	2,133	13	168	272		na	
Zn	5,000	5	28	190	207	20	**62.0**	146		na	
		10	17	113	160	13	**1.84**	0.96	2	27.2	11.7
NO_3^-	50,000	5	2	**1,590**	28.3	1	1,980	0		na	
		10	17	**181**	69.7	8	553	338	1	183	0

[a]*Chemicals Br, Li, Mo, Sb, S, Sr, V were detected but not evaluated due to lack of standard.*
[b]*Bold & shaded text means seasons were significantly different, Wilcoxon Rank Sum test (0.05).*
[c] *Only selected parameters in rainwater were analyzed; collected in October 2013.*
[d] *Std Dev.= 1 standard deviation; Mon= month.*
[e]*No government of Bangladesh (GOB) standard; value is a guideline; SpC units in uS/cm.*
[f] *na=not available.*

Bangladesh has a range for its Cl standard noted as 150-600, and 1,000 mg/l in coastal areas; 1,000 mg/l (1,000,000 ug/l) was used for this comparison [GOB, 1997]. There is no drinking water standard for SpC in Bangladesh. There is, however, a guideline (2,000 uS/cm) that has appeared in the literature and reports for a time [Uddin, 2003; Ravenscroft, 2003; Ravenscroft et al., 2009]. The basis for this guideline is unclear: some sources have indicated that it is a value estimated from regression equations and the upper range of the GOB Cl limit (600 mg/l) [Ravenscroft et al., 2009; Sanchez et al., 2015] while others imply that it may have been derived based on an irrigation water limit for reduced rice yield in Bangladesh [Uddin, 2003]. The GOB guideline for SpC was exceeded in all (100%) of tubewell samples, and pond waters exceeded the GOB guideline for SpC (60% in May, and 9% in October).

The year-wise average Na (a major contributor to SpC) concentrations from P32 were over 370,000 ug/l for ponds, and over 950,000 ug/l for tubewells. Although rainwater sampling was limited, there is a marked difference in all detected concentrations compared to either tubewell or pond water (Table 3.2). In a study conducted by Khan et al. [2014] in Dacope upazila, mean levels of Na in drinking water measured from Kamarkhola and Sutarkhali Unions were 374,000 ug/l and 714,000 ug/l, for all ponds and tubewells, respectively. Khan noted that drinking water with Na levels over 500 mg/L was "exceptionally high", and this level was the equivalent of 27 times the Na limit recommended by the USEPA [USEPA, 2003]. By comparison, Khan's results indicate that residents from P32 face similar, if not higher, health risks from salinity.

All (100%) tubewell samples exceeded the GOB guideline for SpC, as did 60% of pond water samples collected in May and 9% of those collected in October. Sixty three percent (63%) of tubewell samples exceeded the As GOB standard in May, and 53% in October. No surface water samples exceeded the GOB limit for As in May or October, although more exceedances were evident in May (61%) than October (27%) when compared to the WHO limit for As. Regardless of the season, groundwater had more exceedances than surface water in both seasons.

The most frequently exceeded standards (in alphabetical order) for the dry season (May) drinking water samples included (Table 3.3):

- Tubewells (groundwater): Ba, SpC, K, Mg, Na, P

- Ponds (surface water): Ba, F, K, Mg, Na, P

The most frequently exceeded standards for the wet season (October) drinking water samples included (Table 3.3):

- Tubewells (groundwater): Ba, Cl, SpC, Mg, Na, P
- Ponds (surface water): As (WHO limit), Ba, K, Mg, Na, P

No samples exceeded standards for Al, B, Cu, Ni, Zn, or NO_3^-. Exceedances for tubewells as compared to ponds were that tubewells dominantly included SpC and Cl, whereas ponds included F, K, and As (for WHO limit).

From a spatial perspective, all of the sampling locations exceeded standards for multiple chemicals except SW-27 (0 chemicals), and SW-06, and SW-22 (1 chemical). The tubewell locations with the greatest number of exceedances in May were: GW-12, -15, -34, and -39 (also the greatest in October); ponds with the greatest number of exceedances were SW-33 in May, and SW-19 in October. The lowest number of exceedances for tubewells was 6 (GW-30). Figures 3.3 and 3.4 indicate no obvious spatial pattern, other than tubewells have more exceedances than ponds.

3.3.4 Comparisons of arsenic concentrations to national data

As of 2009, it was estimated that 22 million people in Bangladesh are drinking water that does not meet the Bangladesh drinking water standard for arsenic. Furthermore, over 5 million people were at greater risk because they were exposed to water with more than 200 ug/L arsenic [BGS, 2001; BBS, 2011]. P32 was not sampled in the nationwide As surveys conducted from 1999-2003 [BGS, 2001]. Very limited sampling has been performed in the Dacope upazila at large as part of national water surveys since then. In 2009, an extensive national drinking water quality survey (NDWQS) was conducted in Bangladesh as part of the Multiple Indicator Cluster Survey (MICS). The MICS data is used to monitor progress towards achieving the MDGs, and as a basis for policy and program interventions. Water samples were collected for 15,000 household clusters, and aggregated to the District level. Arsenic and 26 other parameters were collected

Table 3.3. Summary of Exceedances of Drinking Water Criteria, 2012-2013

GOB Drinking Water Criterion (ug/l)		Tubewell Samples Exceeding Criterion (%)			Pond Samples Exceeding Criterion (%)		
		Yearly	May	Oct	Yearly	May	Oct
SpC[a]	2,000	100	100	100	33	60	9
Al	200	0	0	0	0	0	0
As	50	59	63	53	0	0	0
		(91)[b]	(96)[b]	(82)[b]	(43)[b]	(61)[b]	(27)[b]
Ba	10	100	100	100	98	100	95
B	1,000	0	0	0	0	0	0
Ca	75,000	64	64	65	17	20	9
Cl	1,000,000	82	71	100	10	90	0
Cu	1,000	0	0	0	0	0	0
F	1,000	78	78	na	43	65	0
Fe	650	67	54	88	0	0	0
K	12,000	96	96	94	81	100	64
Mg	35,000	100	100	100	52	85	23
Mn	100	29	29	29	33	50	15
Na	200,000	100	100	100	71	90	55
Ni	100	0	0	0	0	0	0
P	0	100	100	100	100	100	100
Zn	5,000	0	0	0	0	0	0
NO_3^-	50,000	0	0	0	0	0	0

[a] *Specific conductivity (SpC) guideline in units of uS/cm.*
[b]*The GOB standard and WHO guideline for arsenic were considered separately for the purpose of tallying exceedances. Value in parenthesis is percent exceedance of WHO arsenic guideline, 10 ug/L.*

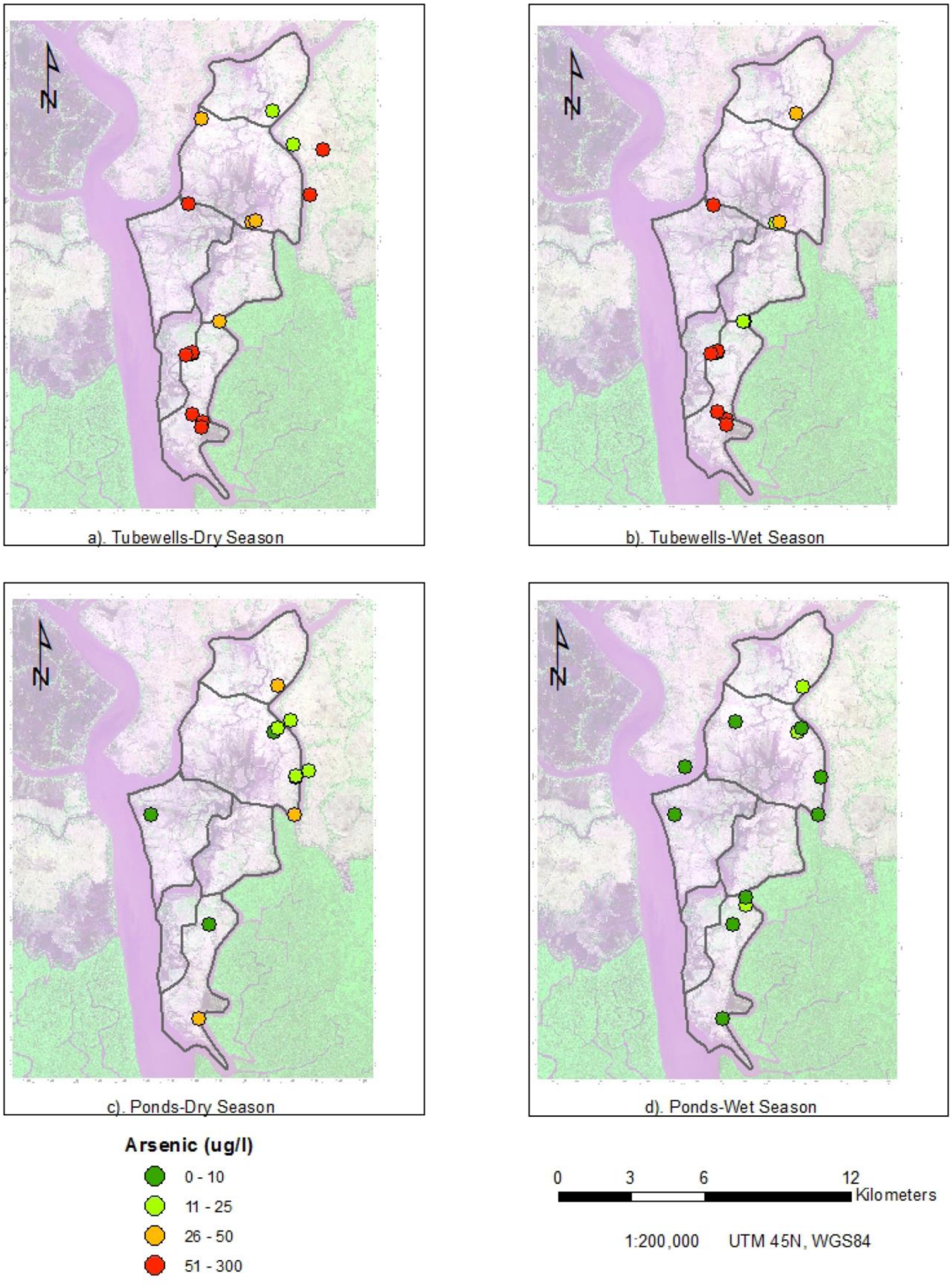

Figure 3.3 Spatial Distribution of Water Quality Results: Arsenic (As)

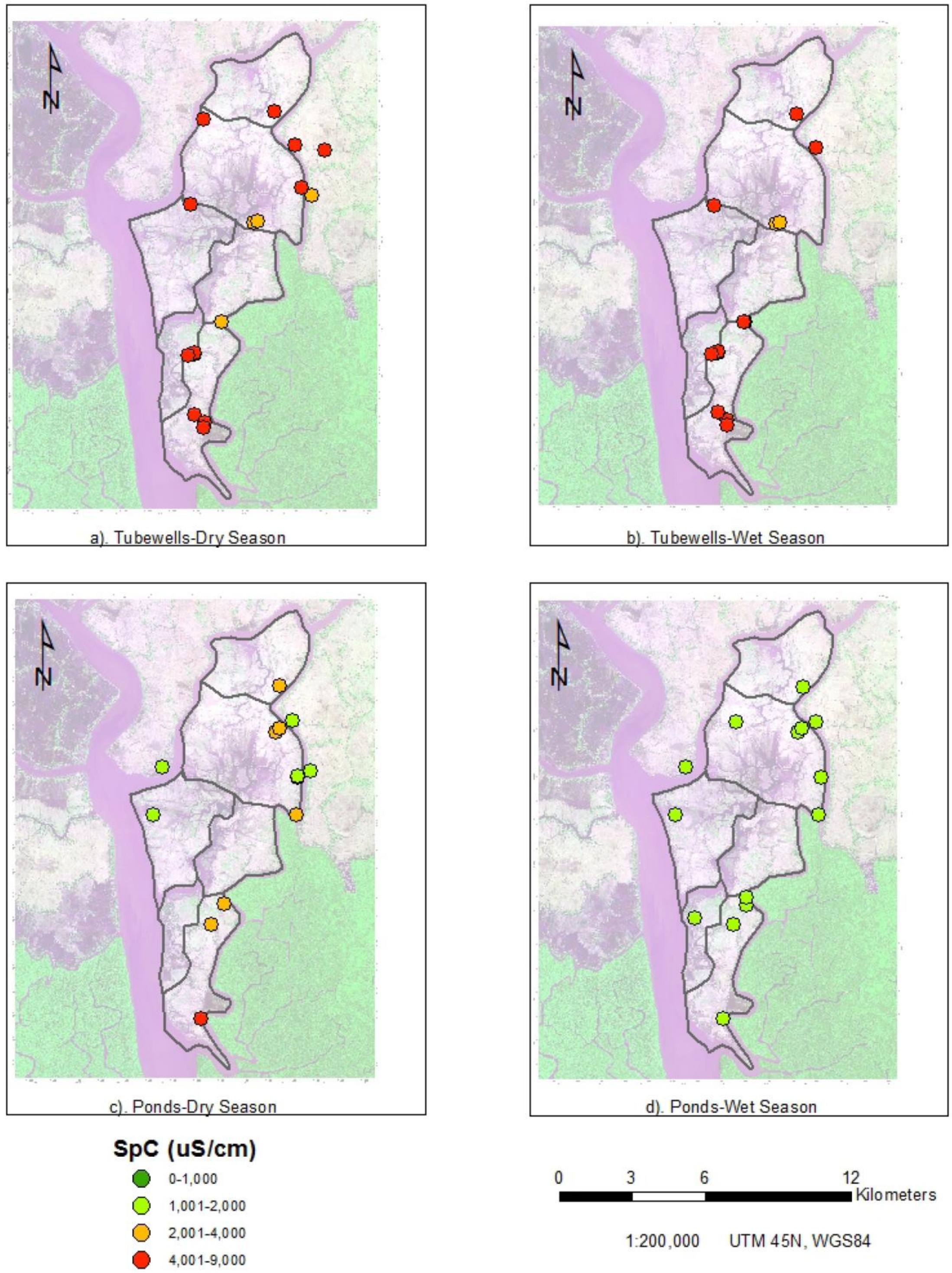

Figure 3.4. Spatial Distribution of Water Quality Results: Specific Conductivity (SpC)

and analyzed, although SpC was not analyzed. The As samples were analyzed by Digital Arsenators, and a subset of samples (about 20%) were analyzed in a lab by ICP-MS [BBS, 2011] for verification. Data "by source" (shallow groundwater, surface water, etc.) are available only at the national level, and only As Arsenator data are available at the upazila level (including Dacope). In order to provide a reasonable comparison with the local P32 results, only the NDWQS lab data are used.

The NDWQS reported that of the samples collected throughout the country and analyzed by Digital Arsenators, 87% met the GOB As limit of 50 ug/L (and 13% exceeded) in 2009, and eighteen of Bangladesh's 64 districts had greater than 20% of the samples above the GOB limit for arsenic; Khulna was not one of the 18 districts [BBS, 2011]. A national average of 27 ug/l was reported for As in the NDWQS. These results were all based on the Arsenator results, for all drinking water sources. Using just the lab data for As, the national drinking water average for all sources was 18 ug/l (8.5% exceeded the GOB standard). Regional averages for As in drinking water were similar: 13 ug/l for Khulna Division, and 10 ug/l for Khulna District (Table 3.4) (BBS, 2011). The national arsenic averages are lower than the locally measured As levels in drinking water (all sources) in the area of P32: 39 ug/l for the North Union (Kamarkhola), 72 ug/l for the South (Sutarkhali) Union, and 24 ug/l for adjacent P33. Results for nearby P31 were much lower (5 ug/l) than the other local results; however, they were based only on surface water sources.

The NDWQS lab results for chemicals other than As indicated that the chemicals that most frequently exceeded the GOB standards were Mn, Fe, and Ca; the chemicals that exceeded the WHO level most frequently were Mn and As. Less than 15% of shallow tubewell drinking water samples met all fifteen GOB drinking water standards. Surface waters were of higher quality, with 30% meeting all fifteen GOB drinking water standards. Overall, shallow tubewells were the source that provided the worst drinking water in terms of chemical quality (excluding microbial contamination), with deep tubewells the second worst [BBS, 2011]. The NDWQS found that As was strongly correlated with Fe and P, and that Na was strongly correlated with Mg, indicating seawater influences in drinking water [BBS, 2011].

Table 3.4. Average Arsenic Concentration in Drinking Water (All Sources)

Geographic Scale	Arsenic Concentration (ug/L)
National[a]	18
Khulna Division	13
Khulna District/Zila	10
Dacope[b]	NA
P32 North Union (Kamarkhola)[c]	39
P32 South Union (Sutarkhali)[c]	72
P31[c]	5
P33[c]	24[d]
GOB Standard	*50*
WHO Level	*10*

[a]*Data from NDWQS (BBS, 2011).*
[b]*Data for Dacope was only available for Arsenator method.*
[c]*Measured data from P32 water quality investigation.*
[d]*Based on surface water sources only.*

3.3.5 Residents' perceptions of water quality

The P32 Ethnosurvey included various questions about residents' perceptions of the quality of their water supplies. When asked if their fields had ever been covered with salt water, collectively the vast majority of the residents from the two mauzas answered "yes" (86%). The residents were asked what they thought the source of saltwater was: cyclone, natural flood, failed embankment, pumped in, or "other". The majority of the residents thought that the source of salt water was from a cyclone (presumably from Aila in 2009). One of the Ethnosurvey questions inquired about whether the quality of residents' water supplies had increased or decreased in 20 years. Collectively for all sources, 42% said there had been a decrease in quality, 39% said they observed an increase in quality, and 20% said they observed no change. Residents were asked if their water had a "bad taste", and the majority (70%) said "no". The water source which was noted to have a "bad taste" most often was ponds (63%). Of those that responded that their main drinking water source was tubewells, only 15.4% thought that the water tasted bad. Of the water sources evaluated, residents were asked if they perceived their water as salty, and the dominant answer was "no" (88%). More people thought that fresh pond water was salty (54%) than thought tubewell water was salty (11%). It is interesting that most of the residents did not perceive the water as having a bad or salty taste, given that 100% of the tubewell samples exceeded the SpC guideline; furthermore, the analytical results indicate that pond water was of higher quality than tubewell water (Tables 3.2 and 3.3).

3.3.6 Problems with potential mitigation measures

There are numerous possible options to address the challenges faced by Bangladesh regarding drinking water insecurity. The obvious technical solution for this rural area is to enhance infrastructure, such as construction of large, community-operated, rain-fed reservoirs; however, anticipated costs and the lack of governance in Bangladesh makes success of this type of resource management doubtful [Gunda et al., 2015]. This was demonstrated by the observation of many poorly maintained and dysfunctional rainwater collection systems on P32.

The switch from surface water in the 1990s in Bangladesh as the primary drinking supply to shallow tubewells greatly reduced deaths from communicable diseases, but led to the realization of the widespread arsenic contamination in shallow groundwater [Ahmed et al., 2006]. Significant research efforts have been devoted to the removal of arsenic from shallow groundwater [Ahmed et al. 2006; Chowdhury 2010]; however, this research does not address the salinity also present in drinking water. Ahmed et al. [2006] suggested that the widespread testing of wells for As was the most effective mitigation measure in reducing people's exposure to arsenic, as it led to a behavioural change in people's selection of water sources; however, this response also does not address salinity. Others have found that the knowledge of which wells had high As concentrations fades quickly, and is inconsequential if the wells are repainted.

Although deep groundwater wells have been shown to provide uncontaminated, “sweet water” in some areas, this is not consistently true throughout the coastal region [Abedin et al., 2014]. Treatment of water is another obvious potential solution to Bangladesh's drinking water problem. However, the costs for treatment beyond PSFs are too great for most rural communities, and municipal sources are rare in the rural areas. Home water treatment is highly variable in developing countries, and essentially not practiced in Bangladesh. Treatment of water at home is correlated with wealth, and coastal Bangladesh is not a wealthy area [WHO & UNICEF 2011; Harun & Kabir, 2013]. Pond sand filters can serve many families and deliver drinking water of higher quality than shallow groundwater, but are less desirable in terms of taste, the inability to treat all contaminants (including salinity), and maintenance requirements.

Community ownership and local leadership can help explain why some rural communities are more water secure than others, primarily because maintenance is addressed locally [Abedin et al., 2014]. Alternatives to groundwater sources for drinking water may improve water security in coastal Bangladesh, but have trade-offs. Increasing household rainwater harvesting reserves appears to be the best solution from a quality and access perspective, but start-up costs are prohibitive to most rural residents, the source is subject to drought, and the number of people served is small [Harun and Kabir, 2013].

3.4 Conclusions

This interdisciplinary study has demonstrated that both groundwater and surface water drinking sources in the southwest coastal area of Bangladesh have levels of arsenic, salinity, and a multitude of other contaminants above Bangladesh's drinking water criteria. It has been shown that aggregation of drinking water data on a national scale masks local differences. Despite claims of achieving the MDG on a national level, the security and sustainability of drinking water supplies at P32 is clearly threatened, and is expected to continue to be as the population increases over time. This paper has demonstrated that assessing social conditions is important to understanding water security at a local level.

Despite the resiliency of the people living on Bangladesh's coast, the efforts of NGOs in this area, and the many years of research that has been conducted, residents on P32 and the region are still faced with water insecurity, and their health and livelihoods continue to suffer. Resolving water insecurity here presents a conundrum. Issues are evident from both the supply and the demand sides, and solutions to this dilemma are not easy or readily evident as they span social, political, environmental, and technical realms. This research has elucidated that the water security problem does not become any less difficult by understanding the water quality in more detail or discerning which mitigation technology that needs to be applied, but rather what is needed is an understanding of how a solution can be successfully *implemented* at P32 and similar areas of rural Bangladesh. Insights for implementation of solutions are gained by the integration of social data in water quality investigations and the collaboration of physical and social scientists. This integrated approach has the most promising outlook for solving the problem of water insecurity in coastal Bangladesh.

As harrowing as the problem of water insecurity is at P32, conditions may be worse at other coastal polders, as well as in other countries. It is imperative to the people of south-western Bangladesh that affordable approaches to providing safe drinking water be developed, and soon. Without water security, there is no food security, energy security is jeopardized, and economic growth and poverty reduction are not sustainable. As human and economic development continues to pressure diminishing water resources, the need for knowledge of concepts, methods, and tools will only increase in an attempt to effectively manage water shortages at Polder 32 and beyond.

3.5 Acknowledgements

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CHAPTER 4

Evaluation of Land Cover at Polder 32 Using Remote Sensing

4.1 Introduction

Asia and the Pacific have some of the highest proportions of degraded land in the world, with vast and expanding arid areas, and the lowest per capita availability of water and arable land [ADB, 2013]. Furthermore, more than 40% of South Asia's arable land is irrigated; this land is directly related to water security, as consumption of water for irrigation makes it unavailable for drinking. Water is an important contributor to food security [ADB, 2013].

Bangladesh's agricultural land is being threatened by natural and anthropogenic land and water use changes over time [Islam, et al., 2015]. In addition to agricultural land degradation, numerous adverse environmental impacts are resulting from land cover changes in Bangladesh: river bank erosion, subsidence, lowered elevation of empoldered land, a decrease in water quality; siltation and sedimentation of river channels, acidification and salinization of soils; elevation rise in channel beds, ecological imbalances, and reduction of flood storage capacity [Islam, 2006; Ali, 2006; Raijitha, et al., 2007; Miah, et al., 2010; Ahmed, 2011; Khan, 2012; Auerbach, et al., 2014; Islam, et al., 2015].

The coastal zone of Bangladesh covers 19 districts in the south and southeast portions of the country, occupies 32% of the land area of Bangladesh, and has about 30% of its population. More than 50% of the coastal population is functionally landless; among the landowners, 80% are small farmers. Coastal livelihoods depend primarily on agricultural, day labor, and fishing-related occupations [Paul & Vogl, 2011; Ahmed, 2011]. The single largest mangrove forest in the world, the Sundarbans, is located in this region; this ecosystem is highly valued, being recognized as both a World Heritage site, and a Ramsar site [Islam, et al., 2015].

Shrimp/fish cultivation has been practiced in coastal Bangladesh for many years. However, it is the relatively recent (starting in the 1980s) intensive and commercialized conversion of agricultural land into shrimp farms that has caused a significant change in the land use/land cover pattern, especially in the south-west [Deb, 1998; Ali, 2006; Islam, 2006; Datta, et al, 2010; Ahmed, 2011; Afroz & Alam, 2013]. Shrimp farming is a highly controversial topic in Bangladesh, and is fraught with issues relating to social conflict, food security, water management, ecological damage and sustainability [Deb, 1998; Islam, 2006; Ahmed, 2011; Paul & Vogl, 2011; Datta, et al, 2010; Islam, et al., 2015].

In Bangladesh, approximately 74-79% of cropped area is under rice cultivation, and the total cropped area for the country is as high as 97% [Xiao, et al., 2006; More & Manjunath, 2013]. Coastal regions contribute only about 16% to the total rice production in the country [Ahmed, 2011]. Land use statistics show that Bangladesh has significant area of land that is either double (27%) and triple-cropped (9%), whereas the Khulna region is primarily single cropped (25%). This difference is most likely because groundwater is suitable for irrigation in areas other than the south-west that extends cultivation into the dry season (Figure 4.1), and because so much of the available land in the south-west is used for aquaculture. It is also notable that the Khulna region has 47% of its land area as forest, due to the presence of the Sundarbans national forest, whereas the country's forested area is only 17% [BBS, 2011].

Fish production includes fish and *chingri*: the freshwater prawn (*Golda*), and the brackish shrimp (*Bagda*), collectively hereafter referred to as "shrimp". Fish production is an important part of Bangladesh's economy, comprising 4% of its GDP in 2012; shrimp accounted for 60% of the value of fish product exports [FAO, 2016]. Shrimp (frozen) exports in Bangladesh for the period of 2006 to 2010 were relatively steady, averaging almost 51,000 metric tons [BBS, 2011]. Figure 4.2 shows the distribution of fish production by culture structure throughout Bangladesh, by district (2009-2010). The major share (about 75%) of shrimp produced in Bangladesh as of 2010 was from the south-western coast, in the Khulna, Satkhira, and Bagerhat districts of the Khulna division [BBS, 2011].

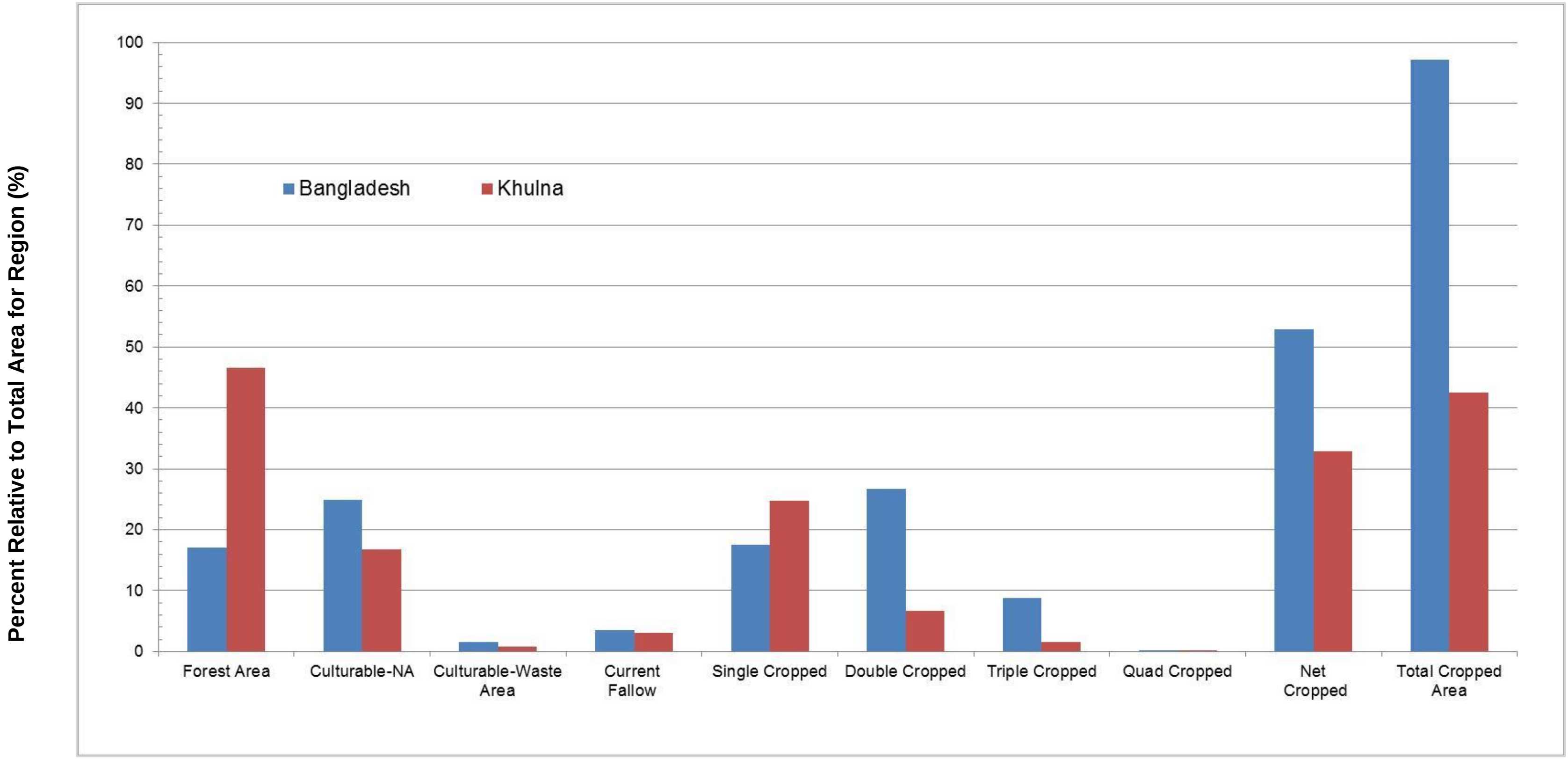
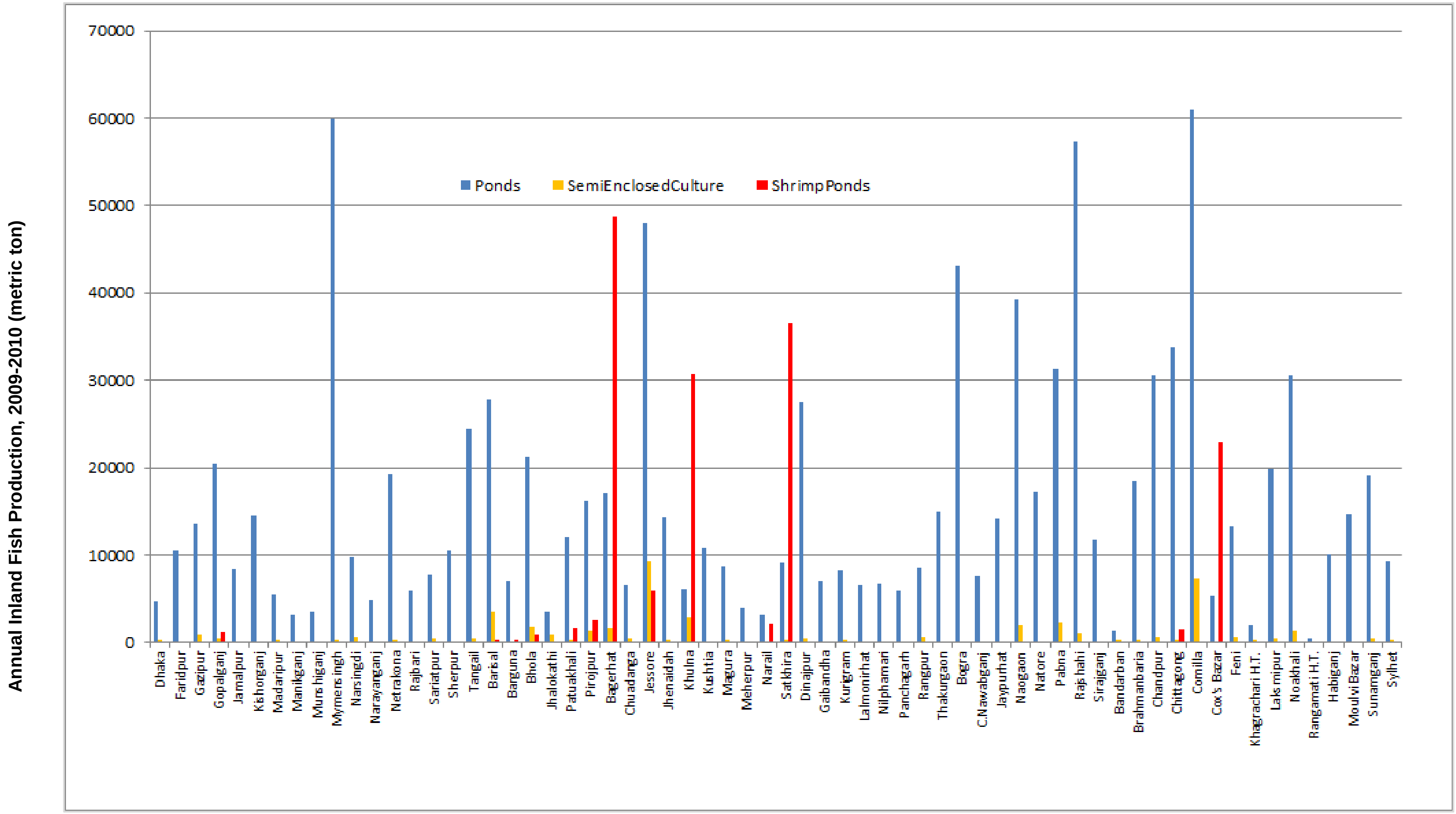


Figure 4.1. Land Use Type in Bangladesh and Khulna Region, 2007-2011

Shrimp cultivation occurs in *ghers*, traditional earthen ponds usually situated near a river, and impounded by an earthen embankment. Most (70%) of the shrimp farms in the coastal area are considered "traditional or extensive," and range from 5 to 10 ha in size (0.05 -0.1 km^2) [Deb, 1998; Paul & Vogl, 2011]. The total area of land under shrimp cultivation in Bangladesh varies greatly, depending upon the source of information. In Dacope, the upazila nearest Polder 32, the number of *Bagda* shrimp ponds was estimated at 10,152, covering an area of 10,339 ha, and the number of *Golda* shrimp ponds was estimated at 155, covering an area of 43 ha in 2003-2004 [Mia & Islam, 2005]. In 2003, it was estimated that there were over 37,000 *Bagda* (brackish shrimp) fields over an area of 170,000 ha in the southwest districts of Satkhira- Bagerhat-Khulna alone [Islam, et al., 2015].

Shrimp/prawn and rice crops are often rotated in response to the natural seasonal salinity fluctuations due to the monsoon (Figure 4.3). In addition, rice and shrimp cultivation may be alternated in the same pond in a given year. In the dry, saline season (January to July), cultivation is focused on *Bagda*, whereas in the low saline season (August to December), freshwater shrimp *Golda* and the slightly salt-tolerant rice, *aman,* are grown [FAO, 2009; Swapan & Gavin, 2011; More & Manjunath, 2013]. Others have reported that *Bagd*a is grown more often where there is access to tidal channels and saltwater, whereas *Golda* is usually grown further inland (Barmon, 2006; Ito, 2004). Farmers do not cultivate *aus* and *boro* rice in the coastal regions [Uddin & Nasrin, 2013]. Figure 4.4 shows a generalized crop calendar for rice and shrimp in south-west Bangladesh, with primary planting and harvest periods relative to the monsoon season [Swapan & Gavin, 2011]. This rotation of crops results in essentially a "dry" period (Jan-June), a "wet" period (June-October), and a growth or "green" period (October-December).

The rate of conversion of agricultural land to shrimp farms is creating a concern for food security in the coastal area. *Bagda* shrimp culture has adversely affected the coastal area by the loss of rice farmland and pond conversion and/or salinization of soil by seepage of salt water, and



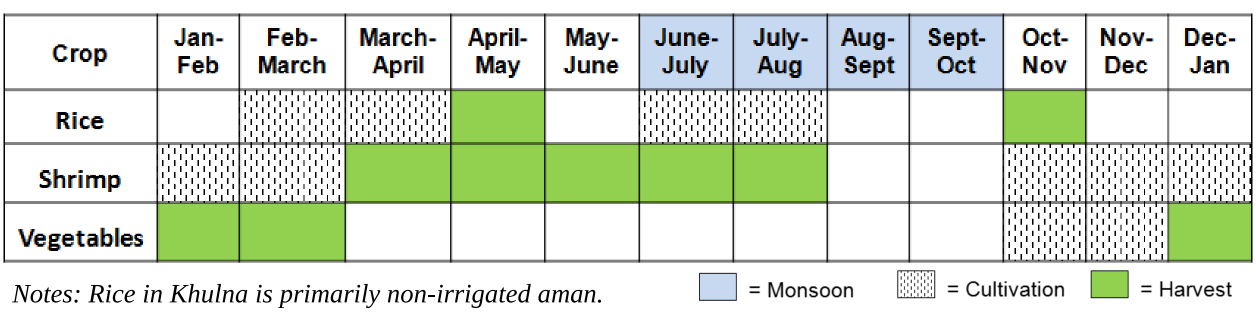
Notes: Most shrimp production in the country is from three coastal districts (shown in red bars), and Cox's Bazar; in order by division (metric ton).

Figure 4.2. Inland Waters Total Annual Production, by District, 2009-2010

Notes: Same Area of Polder 32 Under Shrimp (May 2012) and Rice (October 2012)

Figure 4.3. Alternating Shrimp and Rice Cultivation at Polder 32

disrupted river ecosystems due to harvesting shrimp fry [Paul & Vogl, 2011; Ahmed, 2011; Swapan & Gavin, 2011; Hossain, et al., 2012; Uddin & Nasrin, 2013; Islam, et al., 2015]. In a Soil Resources Development Institute (SRDI) report [Hasan, et al., 2013], it was estimated that Khulna division had a loss of 13,414 ha and 68,760 ha of "agriculture" for the times 1976-2000, and 2000-2010, respectively. "Aquaculture" gains for the same periods for the Khulna division were 5,955 ha and 3,216 ha. In 2006, it was estimated that the area of shrimp farms in Bangladesh exceeded 200,000 hectares. It has been projected that shrimp production has increased 20% per year in the 15-year span from 1983-1997 [Datta, et al., 2010].



Notes: Rice in Khulna is primarily non-irrigated aman.
Source: Swapan & Gavin, 2011

Figure 4.4. Generalized Crop Calendar for South-western Bangladesh

Compared to domestic and industrial discharges in Bangladesh, pollution potential from shrimp a pond effluent is small. However, the problem is amplified because of the large volumes of water discharged from shrimp farms, and the high concentration of farms in areas with limited water supplies and inadequate flushing [Patil, et al., 2002; Raijitha, et al., 2007; Paul & Vogl, 2011]. To maintain suitable conditions for shrimp growth, food, fertilizers, and chemicals are added to the ponds, with 10–40% of pond water exchanged daily. The exchanged water is usually discharged to the adjacent canals, which often is the source of fresh water for nearby agricultural lands. The accumulation of excessive nutrients and organic wastes from the discharge may cause deoxygenation or eutrophication of the receiving waters, and results in the contamination of the sediments by nutrient enrichment and leachate. Highly intensively farmed shrimp ponds may only be productive for 5 years, after which time the contaminated sediments may render the pond unfit for continued shrimp cultivation, and the acidic and saline soils make the land unfit for agriculture [Deb, 1998; Patil, et al., 2002; Raijitha, et al., 2007]. Cultivation of *Golda*, especially when alternated with shrimp has been shown to be much less destructive to the environment (Barmon, 2006).

The rapid expansion of shrimp aquaculture has been attributed to suitable climatic conditions, cheap labor and high profits (Deb, 1998; Paul & Vogl, 2011; Islam, et al., 2015]. Many have embraced the conversion of rice paddy to shrimp farms because the net profit from growing shrimp is about 12 times higher than growing rice [Ali, 2006; Datta, et al, 2010]. Although shrimp farming directly or indirectly employs more than 0.7 million people [Afroz & Alam, 2013], there has been a reduction in livelihoods for the rural population because shrimp farming employs fewer people than rice farming [Swapan & Gavin, 2011]. The result is that many rural areas that once had sustainable rice farming livelihoods have been transformed to producing a commodity for the profit of those that often do not reside in the community [Deb, 1998; Ali, 2006; Swapan & Gavin, 2011; Islam, 2014].

4.1.1 Research Objectives

The objective of this study was to ascertain if a simple method using readily available remote sensing data could be used to quantify the amount of rice paddy converted to shrimp cultivation over the last two decades at Polder 32. The study will help answer the following research questions:

- *What are the patterns of vegetation change over the last 20 years at Polder 32?*
- *Does a shrimp pond have a different spectral signature than a rice paddy?*
- *Does remote sensing at the local level capture the seasonal pattern of rice farming and shrimp cultivation?*
- *Can remote sensing techniques be used to accurately quantify the conversion of rice to shrimp at the local scale?*

4.1.2 Use of Remote Sensing to Assess Land Cover Change

Land use refers to how human beings use the land around them, and the types of activities that involves. Land cover refers to the biophysical characteristics of the land itself. Remote sensing can assess Land cover changes over time, and changes in land use can be inferred by the physical changes to the land observed over time [Jensen, 2007]. Changes in agricultural land use patterns can provide insights to potential impacts on water security over time in an agrarian culture.

Few remote sensing studies were found for south-west Bangladesh; even fewer were found that utilized Landsat data, and none were found that focused on water security, that involve Polder 32, or have been done at the scale of a polder.

Since the 1960s, remote sensing data have been routinely used to evaluate vegetation and associated land use and land cover changes (LULC) [Jensen, 2007; Giri, 2012]. Remote sensing is a cost-effective method of observing land surfaces [Jensen, 2007; Xie, et al., 2008: Giri, 2012]. Classifying and mapping vegetation is important for natural resource management and climate change research, and can be applied from local to global scales, depending upon the sensor used [Jensen, 2007; Xie, et al., 2008].

Remote sensing has been used for decades to estimate crop yield and biomass throughout the world [Jensen, 2007]. Remote sensing has been used at all scales to observe crop growing stages and crop yields [More & Manjunath, 2013]. Cai & Sharma [2010] described a number of remote sensing studies from Asia that evaluated rice productivity, and reported on their research that integrated MODIS sensor imagery, census, and meteorological data to map large-scale yield, evapotranspiration, and water productivity of rice crops for the Indo-Gangetic river basin. Hasan, et al. [2013] prepared a report for the SRDI that used Landsat imagery to estimate land cover changes for the country to get a more accurate estimate of agricultural land productivity. Ali [2006] described the transformation of 79% of land from rice to shrimp from 1985 to 2003 for a village in Satkhira; however, no remote sensing was used.

Dewan & Yamaguchi [2009] evaluated land changes associated with urban expansion in greater Dhaka from 1975-2003 using Landsat data. Their analysis showed that where there was substantial growth of built-up areas, there was also a significant decrease in the area of water bodies, cultivated land, vegetation and wetlands. They performed a regression analysis of factors underlying urbanization and found that expansion was driven by primarily by population growth, elevation, and economic development. Population growth precipitated expansion of land development, preferentially at higher elevations initially, then later at the expense of lowlands and vegetated areas. As population expanded, businesses and industry grew, and land that was previously undeveloped became urbanized.

Although there have been a number of studies performed using remote sensing to study vegetation in southwest Bangladesh, most have focused on mangroves and the Sundarbans [Hossain, et al., 2003; Giri, et al., 2007; Giri, 2012; More & Manjunath, 2013; Kuenzer, et al., 2011; and Rahman, et al., 2013]. Conforth et al., [2013] reviewed the literature regarding remote sensing studies for the Sundarbans; however, their work assessed the health of mangroves using radar.

The most relevant research to this study was reported by Islam, et al. [2015]. They evaluated agricultural land use changed into "wetlands" (including shrimp ponds), and the implications for ecosystem services for three districts of Khulna division: Satkhira, Khulna and Bagerhat. Landsat imagery for four dry seasons (Nov-Jan) from 1980 to 2008 was used to perform a supervised classification and change detection. They found that in a span of 28 years, agricultural land area was reduced by 50%, while the area of "wetlands" increased by over 500%.

4. 1.3 Spectral Characteristics and Indices

Materials on earth constantly absorb and reflect electromagnetic radiation, and thus possess characteristic spectral signatures (**Figure 4.5**). In evaluating land cover, it is important to understand the types of crops that are grown, and how they interact with the climate (their phenology). Chlorophyll pigments in plants are highly absorbed by the red band, and plants are highly reflective (shown as a peak) in the green and near infrared (NIR) bands.

Because standing crops have higher reflectance in the NIR, they appear bright in NIR images due to their moisture content [Jensen, 2007; Xie, et al.,2008]. Healthy, green leaves reflect better in the NIR than when leaves are water stressed, diseased, or dead; under these conditions, they become more yellow and reflect significantly less in the NIR range.

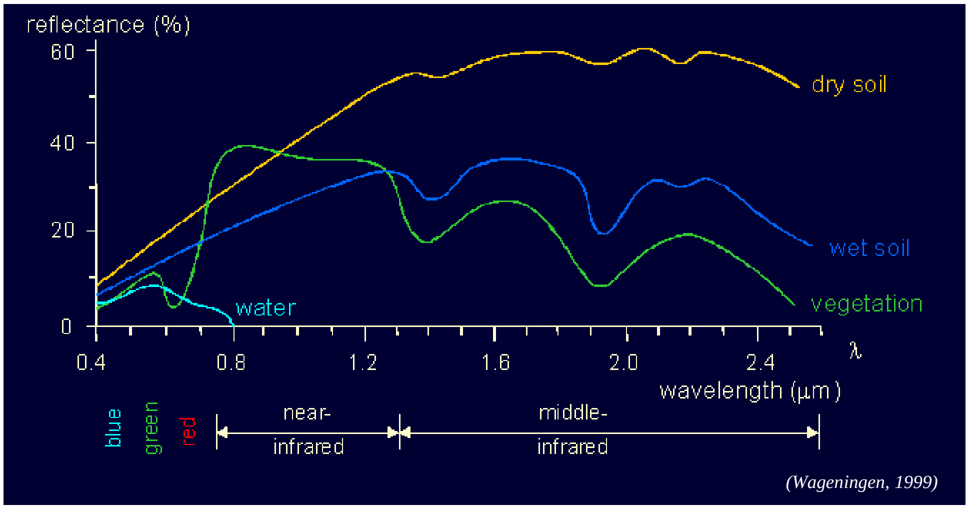


Figure 4.5. Reflectance Spectra of General Land Cover Types

In addition to the reflectance of materials, vegetative indices are often used in remote sensing studies. Vegetative indices indicate the relative abundance and health of vegetation. One advantage of an index is the capability to provide information not available in any single band [Coppin, et al., 2004]. There are many different indices used in a variety of circumstances [Jensen, 2007].

The normalized difference vegetation index (NVDI) is well known and the most widely used index to describe the photosynthetic activity or the "greenness" of vegetation [Jensen, 2007; Giri, 2012; Xie, et al.,2008]. NVDI may be calculated based on the spectral bands from a variety of different multispectral sensors (e.g., Landsat, MODIS), and can be used to observe dynamic changes in specific vegetation over time [Jensen, 2007; Giri, 2012; Xie, et al., 2008]. NVDI has been used extensively at a variety of scales for monitoring vegetation, estimating percent of vegetative cover and vegetation density, monitoring drought, and discriminating between stressed and non-stressed vegetation. It is defined by the following general equation [Jensen, 2007]:

NVDI= (NIR-Red)/(NIR+Red)

Typically, NDVI surface reflectance values vary between -1 and +1 (unitless)[Jensen, 2007]. As a general guide, negative values are recorded for water; very low values (0.1 and below) of NDVI correspond to barren areas of rock, sand, or snow; more moderate values (0.2 to 0.3) represent shrub and grassland, and high values (0.6 to 0.8) indicate highly vegetated areas of temperate and tropical rainforests [Jensen, 2007]. Bare soil or barren land is highly reflective in all Landsat bands [Jensen, 2007]. There are other indices that may be more sensitive to detecting rice than NDVI; however, most involve the use of other sensors (e.g., MODIS) that have more spectral bands [Boschetti, et al., 2014].

4.1.4 Landsat Sensor

Landsat data has been the chief source of imagery for many remote sensing studies because it is free, has a long period of record (over 40 years), and has a relatively high spatial and temporal resolution. In addition, Landsat has a defined orbit, so that the same area on Earth is generally acquired every time the satellite returns to the same location on the earth, meaning that image pairs from multiple dates overlap, which makes Landsat a desirable sensor for change detection studies [Hewson, et al., 2014].

Landsat 5 TM (Thematic Mapper) imagery is available from 1984 to 2011; Landsat 8 (OLI) essentially replaced Landsat 5 in February 2013. Although Landsat 7 imagery is also available for this time period, after May 31, 2003 all Landsat imagery has a problem with the scan line corrector that causes “striping” in the images, and must be corrected or filled with alternative imagery before using in any analyses. Landsat 4 (MSS) imagery has a similar period of record (1982-1993) to Landsat 5, but has some different radiometric properties USGS, 2016a].

The spatial resolution of the visible and near infrared bands in Landsat 5 is 30 m, and the temporal resolution is 16 days; however, images are not usually available for consecutive dates because of cloud cover. Landsat 5 imagery has 7 bands. The near infrared (NIR) band (4) in TM has a wavelength range of 0.75-0.9 μm, and the visible red band (3) has a range of 0.63-0.69 μm (Table 4.1) [Jensen, 2007].

Table 4.1. Landsat 5 Bands and Corresponding Wavelengths[a]

Landsat 5 Bands	Name	Wavelength (um)	Useful for Measuring
1	Blue	0.45-0.52	scattered by the atmosphere and absorbed by chlorophyll, so plants don’t show up well; penetrates clear water illuminates material in shadows; useful for soil/vegetation discrimination, forest type mapping, and identifying man-made features
2	Green	0.52-0.60	penetrates clear water fairly well, gives excellent contrast between clear and turbid (muddy) water
3	Red	0.63-0.69	limited water penetration; reflects well from dead foliage, but not well from live foliage; useful for identifying vegetation types, soils, and urban (city and town) features
4	Near Infrared (NIR)	0.76-0.90	very good at detecting and analyzing vegetation; good for shorelines and biomass estimation
5	Shortwave IR (SWIR) 1	1.55-1.75	limited cloud penetration; useful for measuring moisture content of soil and vegetation; good for differentiating between snow and clouds
6	Thermal IR[b]	10.40-12.50	primarily for observing temperature and its effects, sometimes used to identify vegetation density & moisture
7	Shortwave IR (SWIR) 2	2.08-2.35	limited cloud penetration; provides good contrast between different types of vegetation; useful for measuring the moisture content of soil and vegetation; helps differentiate between snow and clouds

Notes: [a]Source: IGETT, 2016
[b]Thermal band was not used in this study.

The consideration of the spatial resolution of imagery is critical, because the resolution must be small enough to detect the changes of interest. A rule of thumb often cited is that the spatial resolution of the imagery should be at least half the size of the scale of changes to be observed. For example, a 30 m resolution for Landsat represents a ground area of 900 m^2 (30 m x 30 m), so 1 ha would be represented by 11 pixels for Landsat 5. Sensors with coarser spatial resolutions such as MODIS (250-1,000 m resolution) are not suitable for land-cover monitoring because smaller-scale changes will not be discernable [Hewson, et al., 2014].

4.1.5 Image Pre-Processing

Imagery must be pre-processed before undertaking analysis of the images. Pre-processing usually involves geometric correction and radiometric correction (including atmospheric correction). Ground conditions, seasonal phenology, and atmospheric conditions and other factors can contribute to variability in spectral responses that is not related the remote sensed objects themselves [Song, et al., 2001; Xie, et al., 2008]. Geometric correction includes the selection of a map projection system and may involve the coregistration of images with each other, or with other imagery that is used for reference [Xie, et al., 2008]. Radiometric correction is related to the sensor and its relationship to the earth, including solar illumination conditions, sun angle, atmospheric scattering and absorption, and detector position and performance. Most radiometric corrections involve conversion from digital number detected at the sensor, to radiance, then reflectance, at the top of atmosphere (TOA), and/or reflectance at the surface of the earth [Coppin, et al., 2004].

Considerable research has been undertaken to quantify and correct the effects of atmospheric interference. Atmospheric correction is considered necessary for performing multi date change detection and for use of vegetation indices [Song, et al., 2001; Jensen, 2016]. However, the difficulty in obtaining detailed physical measurements for advanced models, especially for historical imagery, is well recognized [Coppin, et al., 2004; Xie, et al., 2008]. It has been shown that the more complicated atmospheric correction algorithms do not always lead to greater accuracy. A commonly used correction is dark object subtraction (DOS) with or without a Rayleigh atmospheric correction (absolute routine), or atmospheric normalization (relative routine) [Coppin, et al., 2004].

There are now surface reflectance products and vegetation indices that have been atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS); these products are currently considered provisional [USGS, 2016b]. The LEDAPS algorithm applies MODIS sensor atmospheric correction routines to the Level-1 data products to convert TOA to surface reflectance. Information on water vapor, aerosol optical thickness, ozone, geopotential height, atmospheric pressure, a topography-dependent Rayleigh scattering correction, and digital elevation data are input into the "6S" (Second Simulation of a Satellite Signal in the Solar Spectrum) radiative transfer model to generate a surface reflectance for each pixel [USGS, 2016b]. The LEDAPS data require that a scale factor of 0.0001 be applied to obtain surface reflectance values, so the axes of figures of surface reflectance are noted as " x 10,000". The use of already prepared surface reflectance products reduces the possible errors and differences in pre-processing imagery.

4.1.6 Classification and Change Detection

Remote sensing studies often involve change detection analyses. Change detection methods have spatial, spectral, and temporal considerations. The type of method chosen and the period over which it is implemented has a profound effect on the resultant estimates of disturbance, and thus the conclusions, based on the change analysis. Many change detection methods are on a per-pixel analysis, based on the information contained in the spectral and radiometric characteristics of the images. Other methods involve using groups of pixels or segments, called object-based classification [Jensen, 2007].

Classification is a common remote sensing task. This refers to the process by which all pixels in an image are categorized into recognizable land cover "classes". Classifications may be unsupervised, supervised, or other. Unsupervised classification methods rely strictly on pixel-based spectral statistics. In supervised classification, the user applies specific knowledge of the data and study area, as well as pattern recognition skills to help the software determine spectral signatures for data classification [Jensen, 2007].

There are many different classifying algorithms. Classifiers may be discrete, probability-based, or fuzzy. The most widely used supervised classification is the Maximum Likelihood Classification (MLC)[Richards & Jia, 2006; Xie, et al., 2008]. This algorithm is probability based, and relies on the statistical distribution pattern of the image. MLC assumes normality, and calculates probability distributions for the classes related to Bayes' theorem, determining if a pixel belongs to a certain land cover class. The probability distributions for the classes are in the form of multivariate normal models [Richards & Jia, 2006].

For best implementation of MLC, an adequate number of pixels is required for each training area to calculate the covariance matrix. The discriminant function, described by Richards and Jia [2006], is calculated for every pixel as:

$$g_k(x) = \ln p(C_k) - \frac{1}{2}\ln|\Sigma_k| - \frac{1}{2}(x - y_k)^t \Sigma_k^{-1}(x - y_k)$$

where:

- C_k = land cover class k;
- x = spectral signature vector of a image pixel;
- $p(C_k)$ = probability that the correct class is C_k;
- $|\Sigma_k|$ = determinant of the covariance matrix of the data in class C_k;
- Σ_k^{-1} = inverse of the covariance matrix;
- y_k = spectral signature vector of class k.

Therefore:

$$x \in C_k \iff g_k(x) > g_j(x) \forall k \neq j$$

To perform a supervised classification, it is necessary to create "training areas" or regions of interest (ROIs) representative of the classes or types of features of interest to the study (e.g., trees, water, developed areas). The types and number of classes chosen depends upon the objectives of the study, the imagery used, and resources available. It is important that the classes and training areas span the range of observed features and reflectances in the image. The goal in the selection of classes and training areas is to determine the appropriate features and numbers to satisfy the question being pursued with minimum time and effort, and to obtain optimum separability between classes in order to provide a unique signature for use in the classification.

The classification should be complete (i.e., by covering all surface types), and mutually exclusive (i.e., a feature cannot be classed as more than one type) [Jensen, 2007].

It has also been suggested that the selection of training areas should be dependent upon the type of classifier used [Foody, 2002]. However, Li, et al [2014] tested 15 different classification algorithms using Landsat data and found that lack of a sufficient number of training samples led to more classification inaccuracies than the algorithms themselves. Their study indicated that the best classification accuracy for images with 6 bands was achieved by logistic regression, followed closely by the MLC.

The recommended minimum number of training pixels for ROIs varies widely, from 10n to 100n (where n is the number of spectral bands)[Richards & Jai, 2006; Congalton & Green, 2008]. Li, et al. [2014] summarized that 10-30n was sufficient for classifiers such as MLC that require few input parameters; they were able to achieve good results using only 60 pixels per class.

4.1.7 Selection of ROI and Separability of Classes

The separability of training classes can be assessed in a variety of ways. Two methods present in ENVI tools are the Jeffries-Matusita (JM) Distance statistic and Transformed Divergence. Both are used to assess the potential to discriminate between two different classes. Assuming multi-variate normal distributions, the JM distance is defined as:

$$\mathrm{J\text{-}M}_{ub} = \sqrt{2(1-e^{-\alpha})}$$

$$\alpha = \frac{1}{8}(\boldsymbol{\mu}_u - \boldsymbol{\mu}_b)^T \left(\frac{\mathbf{C}_u + \mathbf{C}_b}{2}\right)^{-1} (\boldsymbol{\mu}_u - \boldsymbol{\mu}_b) + \frac{1}{2}\ln\left[\frac{\frac{1}{2}\left|\mathbf{C}_u + \mathbf{C}_b\right|}{\sqrt{\left|\mathbf{C}_u\right| \times \left|\mathbf{C}_b\right|}}\right]$$

Where :
u and *b* = the two region classes
Cu is the covariance matrix of u,
μu is the mean vector of u,
T is the transposition function

The range of values for the JM statistic is 0 to 2; well-separated values exceed 1.9.

Change detection methods may combine both change extraction (change detection algorithm) and change separation (classification routine) [Coppin, et al., 2004]. There are many change detection methodologies currently in use. The most common imagery-based change detection techniques include principle component analysis (PCA), image differencing, and post-classification image differencing [Lu et al., 2004; Jensen 2007]. Other common change detection techniques include vegetative index differencing, change vector analysis, and tasseled-cap analysis [Jensen 2007]. Post-classification change detection is the most commonly used quantitative method of change detection, according to Jensen [2007]. Post-classification methods constitute a "from-to" type of analysis in which information about land cover types are evaluated before and after the change over time.

It is recommended that the results of image classification be compared to reference data to judge the "correctness" of the method. This is often achieved by use of an "accuracy assessment" [Congalton & Green, 2009; Foody, 2002]. The main component of an accuracy assessment is the error matrix (or confusion matrix). The error matrix shows the overall accuracy, the producer’s accuracy, and the user’s accuracy for each class [Congalton & Green, 2009; Foody, 2002; Jensen 2007; Xie, et al., 2008; Hewson, et al., 2014]. Overall accuracy is the portion of the total number of correctly mapped pixels. The producer’s accuracy indicates how often a pixel is correctly assigned to a specific class. This statistic is based on errors of omission, i.e., how often a pixel was incorrectly omitted from the class. The user’s accuracy indicates how often a pixel was incorrectly assigned to a given class. This is based on errors of commission, i.e., how often a pixel was incorrectly included in a class [Hewson, et al., 2014]. The Kappa coefficient is sometimes also calculated, but there are many limitations with this statistic [Foody, 2002; Hewson, et al., 2014]. Reference data may include thematic land use maps (if available);

points collected from site-specific field data or higher resolution imagery such as GeoEye, Quickbird, or Google Earth [Giri, et al., 2007; Gumma, et al., 2011; Rahman, et al., 2013; Aggarwal, 2015]. There are no agreed "standards" or acceptance limits for accuracy, but Thomlinson et al. [1999] suggested a target overall accuracy of 85%, with no class less than 70% accurate [Foody, 2002]. The results of the error matrix can be used to guide refinements to the analysis.

This study involves the use of surface reflectances and the MLC supervised classification and post classification change detection of Landsat imagery over time, as well as NDVI estimates over time, in an attempt to evaluate the change in agricultural land and shrimp ponds in the area of Polder 32. This analysis is intended to provide an indirect appraisal of possible impacts to water security on a local scale, using readily available imagery.

4.2 Methods & Materials

The software used included ENVI 5.3, ArcGIS 10.3.1, and the open-source QGIS. Because of the small size of the features of interest at Polder 32, it was determined that imagery from the Landsat sensor, with its 30 m spatial resolution, would be the most feasible for this task. In order to minimize differences due to type of sensor, clouds, phenology, and atmospheric interference, it was decided that only cloud-free Landsat 5 images would be used.

All available Landsat 5 Thematic Mapper (TM) images from 1987 to 2011 were reviewed to obtain imagery from both the "dry" and "green" portions of the year. Images are identified by the year and day of the year of their acquisition, e.g., 1989358 is Dates with the last 3 digits > 300 are considered to be the green season; those with < 100 are considered dry season. The selected images were obtained by request to the USGS Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) On Demand Interface [USGS, 2016c].

Of over 50 images downloaded, eleven (11) cloud-free dates were identified for green and dry periods of the year for WRS paths 138/137, rows 44/45, collectively. All images were "L1T" level products, meaning they have been geometrically corrected using precision ground control points and elevations from the Shuttle Radar Topography Mission (SRTM), yielding a dataset with accuracies within 30 m, thus eliminating the need for further geometric correction [Hewson, et al., 2014]. The 11 Landsat 5 images used in this study are listed in Table 4.2. The tidal level relative to the datum EGM96 in centimeters (cm) is given for the collection time (local) of the image, as well as the lowest and highest tides that day.

The 11 Landsat 5 images obtained were initially evaluated by observing individual surface reflectance bands in ENVI 5.3. All images were pre-processed by checking for correct geometric registration; reprojection (if necessary) to the same projection (UTM 45N, WGS84), stacking bands into one multi-band image by date, and then clipping to a common extent that encompassed Polder 32.

Table 4.2. Landsat Images Used

Image, by Year & Ordinal Date	Date	Path & Row	Tidal Level at Image Collection (cm)[d]	Lowest Daily Tide on Date (cm)	Highest Daily Tide on Date (cm)
1987358	12/24/1987	138044	-17	-84	215
1988329 [a]	11/25/1988	138044	-42	-48	236
1989075 [a]	3/16/1989	138044	62	-48	120
1989315 [b]	11/11/1989	138044	132	-75	230
1991314	11/10/1991	137044	-54	-75	215
1999352	12/18/1999	137045	205	-40	229
2006026 [c]	1/26/2006	138044	126-144	-58	186
2008313	11/9/2008	137045	-42	-61	307
2009082 [a]	3/23/2009	138044	120-169	-51	236
2011040	2/9/2011	138044	-3 - -37	-54	231
2011312 [a]	11/8/2011	138044	147-202	-48	242

Notes: Dates with the last 3 digits > 300 are green season, those with < 100 are dry season.
[a]*Used in classification.*
[b]*Used in surface reflectance, but not NDVI.*
[c]*Used in NDVI, but not surface reflectance.*
[d]*For Mongla, local time, relative to EGM96.*

All of the NDVI surface reflectance images were preprocessed in the same way as the surface reflectance bands, but then were stacked into one multi-date stack. Although all of the images were noted as "cloud free" and atmospherically corrected, some bands in the images were observed to have blurry or hazy regions, or have other artifacts or possible errors. As a result, one image was excluded from surface reflectance analysis (2006026), and one from the NDVI analysis (1989315).

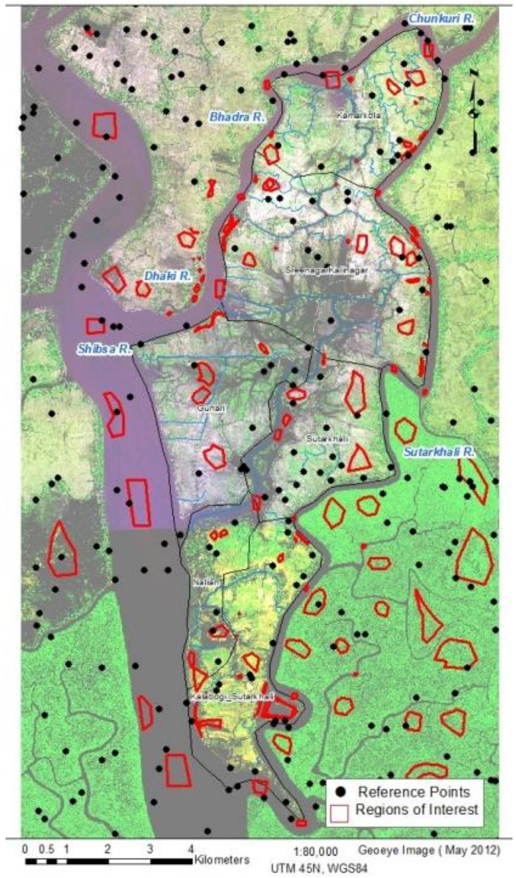


Figure 4.6. Location of ROIs and Reference Points

The training areas (ROIs) for classification for this study were created using the 2011 Landsat images viewed in false color (RGB bands=432, 2% stretch) to maximize observation of vegetation, while also viewing a high resolution (0.5 m) May 2012 Geoeye image. Figure 4.6 shows the location of the ROIs as well as the reference points used in the accuracy assessment.

After trial and error, the following five land cover classes were determined to be the most useful in this analysis:

- **Water**: included major rivers, as well as inland channels, and channels in the Sundarbans
- **Developed**: included the embankments and buildings
- **Mangroves**: refers to various locations in the adjacent Sundarbans; no distinction in upper and lower canopy
- **Rice/Crops**: areas where rice was known to have been cultivated during the green season; this also includes barren land in areas where no crops are grown
- **Shrimp Ponds**: collectively, all ponds are considered shrimp pond for this analysis; spectral signature was based on known locations of shrimp cultivation; class also includes fish ponds, drinking water ponds, and bathing ponds, as they could not definitively be distinguished in the Landsat imagery.

Figure 4.7 shows the difference in resolution for each of the land cover classes in the high resolution 2012 Geoeye image and the corresponding Landsat image.

A supervised classification was performed for two dates using the MLC in ENVI for the dry and green seasons. The Time 1 images were 1989075 and 1988329, and the Time 2 images were 2009082 and 2011312. Following classification, post-classification change detection procedures were conducted. A local majority 3 x 3 pixel filter was applied to the final classified images to remove residual "speckles" and spurious pixels. The filter re-assigns values based on the class value of the majority of the pixels in each 3 x 3 window. An accuracy assessment was then performed using the highest resolution imagery available closest to the test imagery date to produce an error matrix.

4.3 Results

Figure 4.8 shows the 10 images evaluated for surface reflectance in order by date (1987-2011), represented as a pseudo natural color composite (RGB=742 bands, 2% stretch). In this composite, healthy vegetation appears green, pink areas represent barren land, sparsely vegetated or dry areas are orange and brown, water is blue, and soil may be a variety of colors.

4.3.1 Physical Observations, 1987-2011

It is evident from Figure 4.8 that many physical changes have occurred on Polder 32 over the 24 years that were evaluated in this study. However, observations are speculative since the Polder is an extremely dynamic environment, and it is difficult to ascertain from remote imagery the nature of the changes that have occurred. It is likely that many of the differences in the images can be explained by tidal stage (see Table 4.2), the date of the image relative to recent cyclones, and perhaps other environmental phenomenon. It appears that early 1989 (ordinal date 075) may have been the first introduction of shrimp farming on a larger scale, as many small dark rectangles are present, although it was reported to occur earlier in this area (Datta, et al., 2010). Later in 1989 (ordinal date 315), it appears as if a flood event or perhaps storm surge caused widespread flooding or waterlogging throughout the polder. Both of the 1989 images were taken at a relatively high tidal stage (Table 4.2).

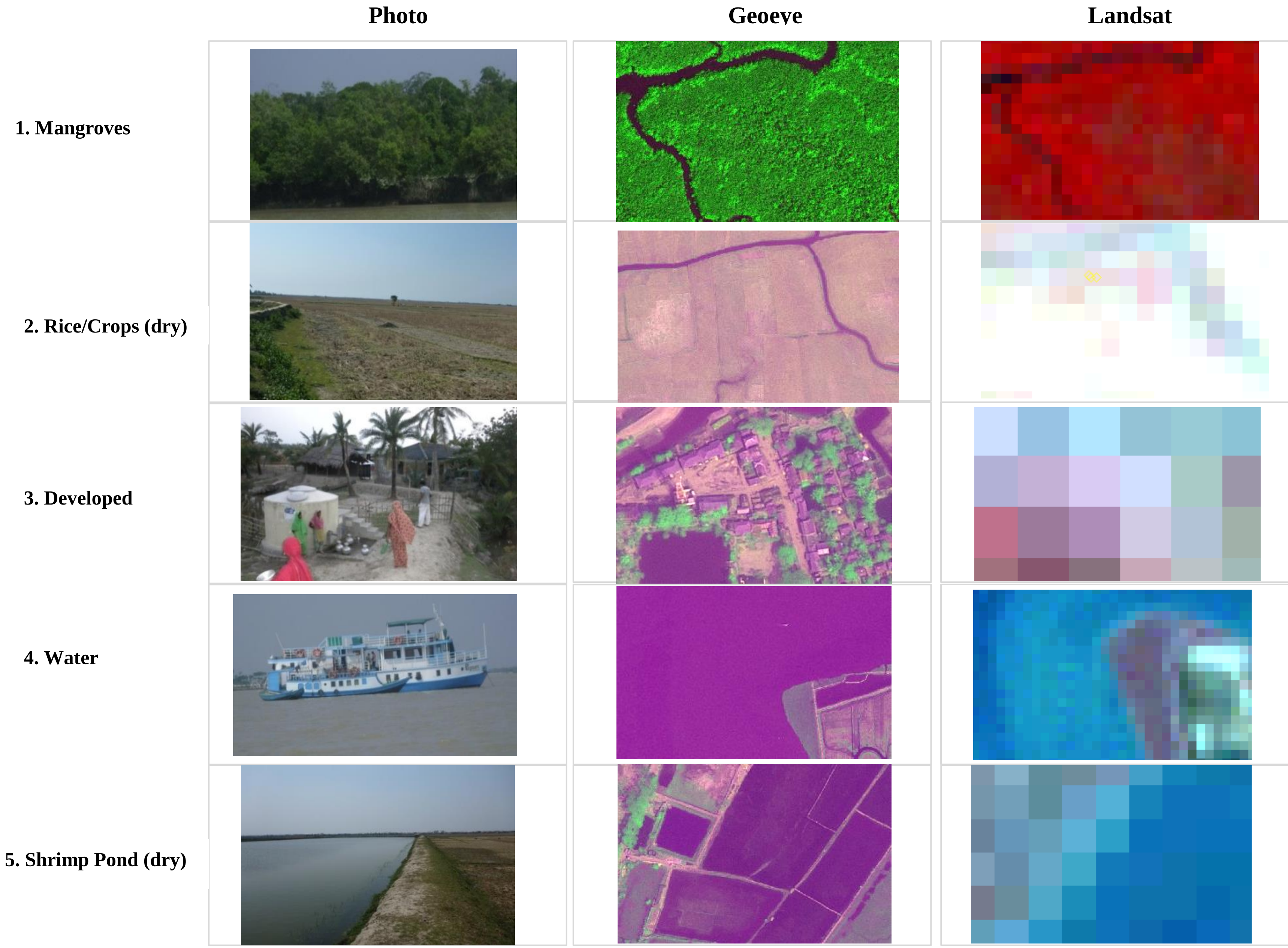


Figure 4.7. Examples of the Five Classes and Representation in Imagery

There is a large pink area in the southeast portion of the 1991314 image (taken at low tide) that may indicate a construction project of some kind.

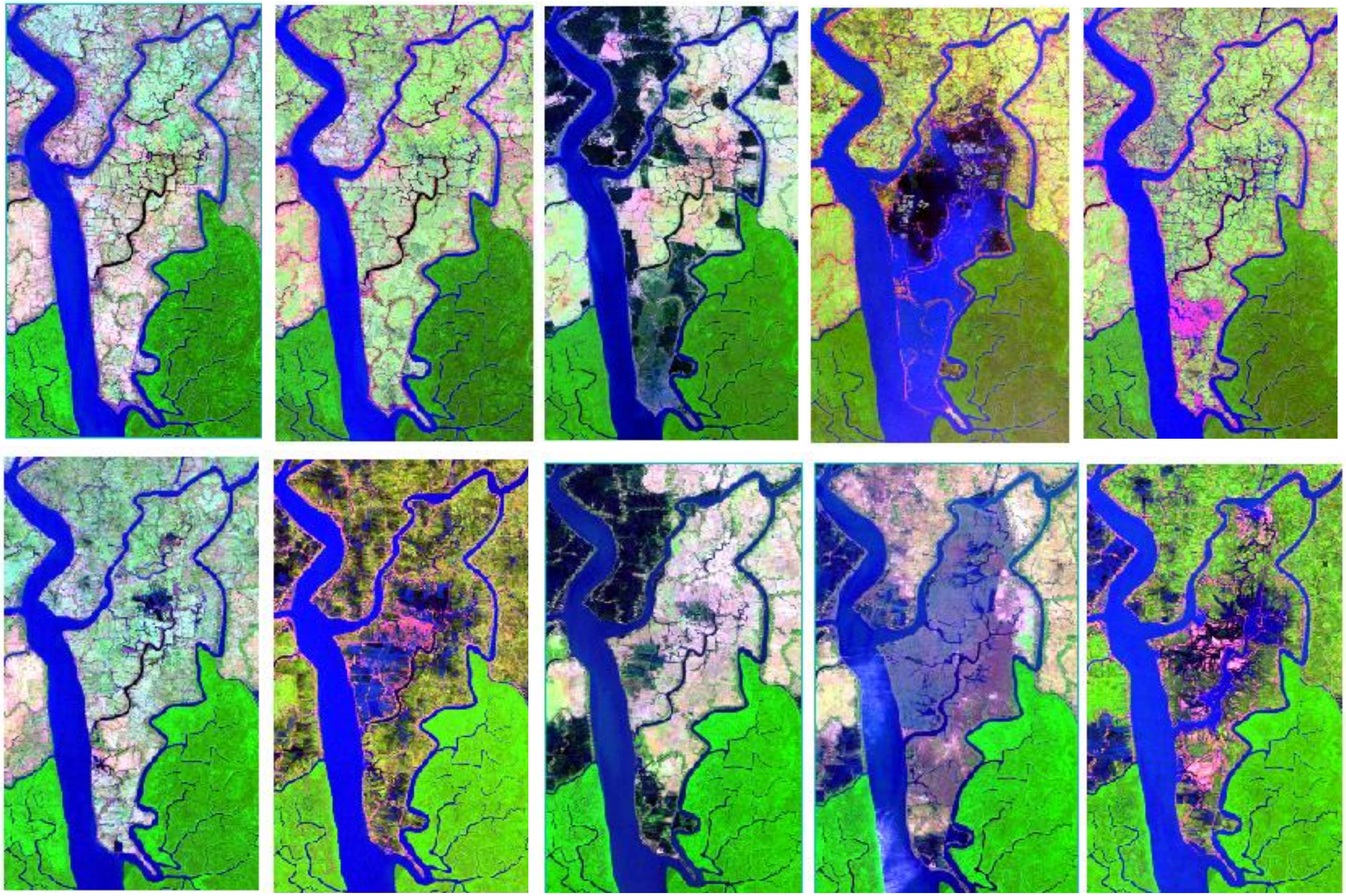
The presence of water throughout the center of the polder in the 2008313 image may be the result of waterlogging from cyclone Sidr that occurred the year before (Nov. 15, 2007). This apparent extent of water throughout this image is especially interesting considering it was taken at low tide (see Table 4.2).

The 2009082 image was taken at a relatively high tidal stage, before cyclone Aila, which occurred in May 25, 2009 (ordinal date 2009145). Cyclone Aila devastated the southwest coast, and Polder 32 was impacted especially hard. Storm surge reached 2-3 m above sea level [Hossain, et al., 2012]. Many embankments were breached which resulted in loss of life, land, livestock, and livelihoods, as well as the salinization of drinking water supplies and soil, and extensive water-logging of the land. Many Polder 32 residents were forced to move their residences to the embankments that remained in tact.

Significant changes to inland channel width are obvious in 2011 when the 2011040 (taken at low tide) image is compared to the 2011312 image (taken at high tide). It is interesting that the difference in the appearance of the 2011 images is more significant than the images "before and after" Aila; this may be due to the difference in tidal stages in the 2011 images. In the 2011040 image, the northeast side of Polder 32 looks drier than the rest of the polder; evidently, an inland embankment saved the north end of the polder from flooding. There appears to be some atmospheric effect like haze (presumably from a LEDAPS processing error) that contributes to the strange representation of features in the 1989315 and 201140 images.

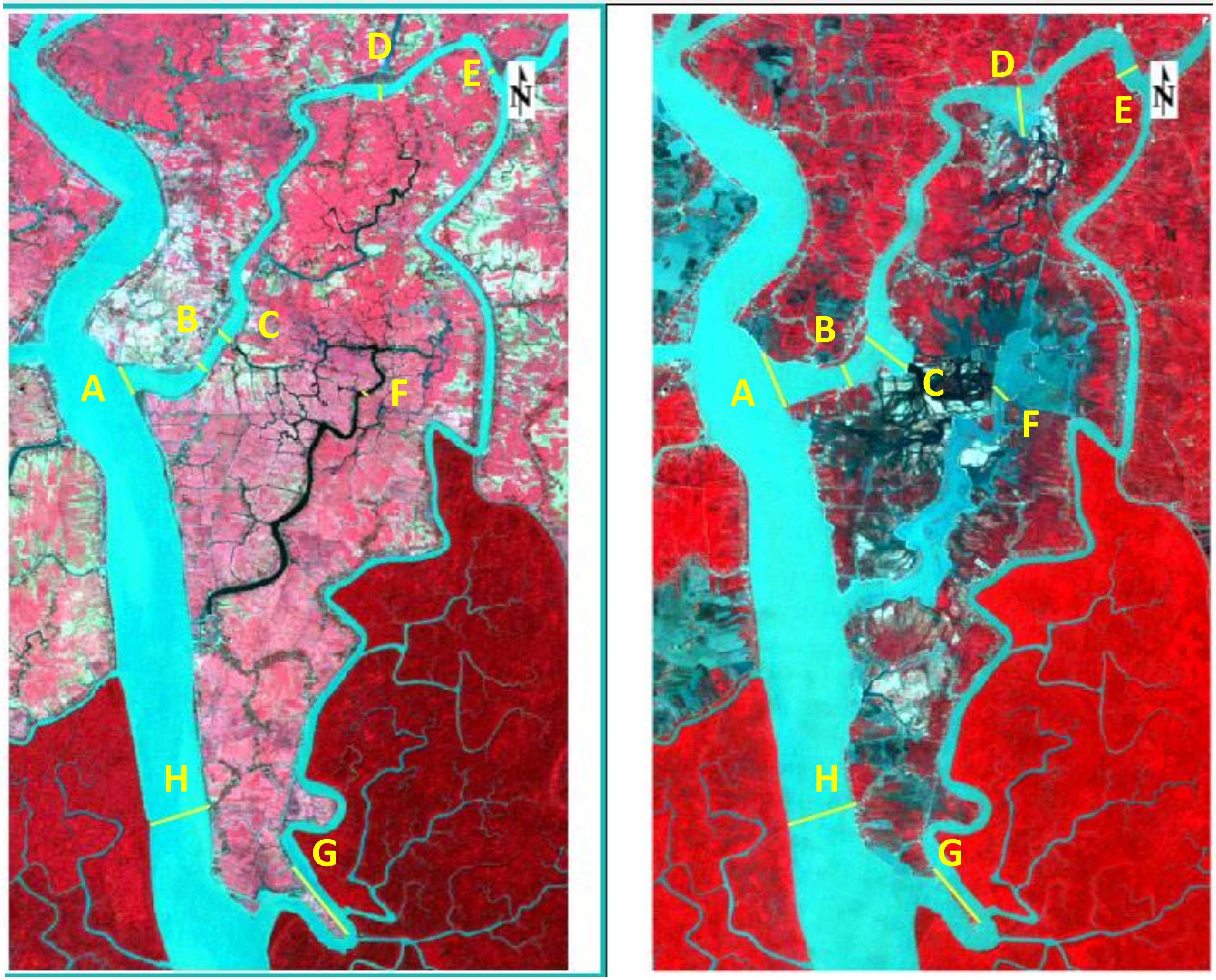
Closer examination of the images from 1988 and 2011 reveal a number of physical changes that have occurred on Polder 32, including erosion of shoreline, and widening as well as siltation of the stream channels (Figure 4.9). At specific measured locations A through H, channel widths increased from 300 to almost 800 m from 1988 to 2011(Table 4.3). In general, the eastern side of the polder and the Sundarbans show much less change than the rest of the polder.

1987358 1988329 1989075 1989315 1991314



1999352 2008313 2009082 2011040 2011312

Figure 4.8. Surface Reflectance Imagery of Polder 32, 1987-2012



Notes: Lettered areas correspond to Table 4.3. Surface reflectance images 1988329 & 2011312 represented as RGB= 4,3,2, 2% stretch. Scale is 1:100,000.

Figure 4.9. Physical Changes on Polder 32, 1988 to 2011

Areas A through C show a widening of the confluence of the Shibsa and Dhaki rivers, and continued widening upriver on the Dhaki, as well as a change in shape of the northwest edge of Polder 32. Areas D and E also show a significant change in the shape of the northeast corner of Polder 32, a widening of the northern portion of the Bhadra river, as well as a change in shape of the Chunkuri river channel at the confluence with the Bhadra river. Area F shows an extreme widening of the inland channels in the center of Polder 32. Area G shows how the southern most tip of Polder 32 has eroded, and area H shows a widening of the southern portion of the Shibsa river adjacent to Polder 32.

Table 4.3. Changes in Physical Measurements Selected Areas, 1988-2011

	Length of Segment (m)		
Area	**1988329**	**2011312**	**Change (m)**
A	670	1253	+583
B	287	571	+284
C	339	1130	+791
D	441	1079	+638
E	167	470	+303
F	135	440	+305
G	1814	1494	-320
H	1367	1500	+133

Notes: See Figure 4.9 for locations of segments.

The closest meteorological station to Polder 32 maintained by the Bangladesh Meteorological Department (BMD) is located at Mongla (see Figure 1.1 for location). Figure 4.10 shows the available monthly mean rainfall data (in mm) for Mongla, from 1991-2012, as well as the 12 month standard precipitation index (SPI) for the same time period.

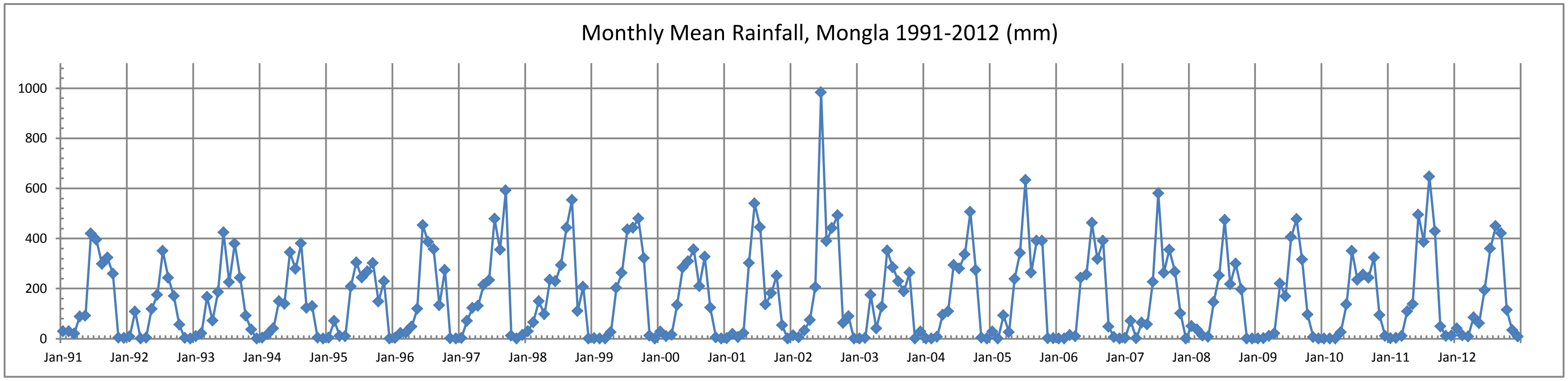
The SPI is a widely used tool for monitoring drought and anomalous wet events [WMO, 2012; Shahid, 2010], and is used by the Bangladesh Meteorological Department. The SPI, introduced by McKee, et al. [1993] is based on the cumulative probability of a given rainfall event occurring at a station. SPI is computed by dividing the difference between the normalized seasonal precipitation and its long-term seasonal mean by the standard deviation. Historic rainfall data for the station are normalized using a gamma distribution through the process of maximum likelihood estimation of the gamma distribution. The SPI can be calculated for 1 to 72 months. A 12-month SPI is a comparison of the precipitation for 12 consecutive months with that recorded in the same 12 consecutive months in all previous years of available data. Positive SPI values indicate wet conditions greater than median precipitation, and negative values indicate dry conditions less than median precipitation. The SPI was calculated using the program available from the National Drought Mitigation Center [2016]. The categories used to describe SPI values are given in Table 4.4 [WMO, 2012]:

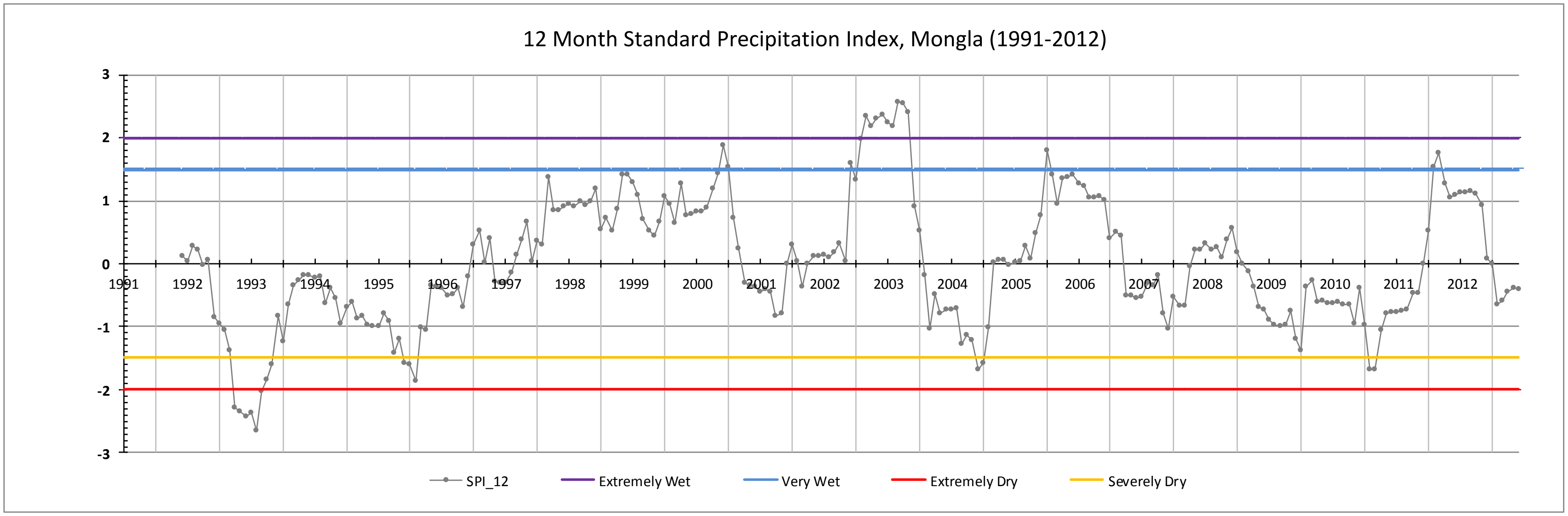
Table 4.4. SPI Categories

SPI Value	Category
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2.0 and less	Extremely dry

The monthly mean rainfall plot reflects the monsoon climate, with most of the precipitation occurring between May and October. The maximum monthly precipitation occurred in June 2002 (983 mm) (**Appendix A**); SPI values for this period were classified as extremely wet. The maximum monthly rainfall for most of the other years was less than 600 mm. Per the 12 month SPI, extremely dry conditions were observed in 1993, and extremely wet conditions occurred in 2003.

None of the 11 images used for this study were available for any of these anomalous years to show the potential effects this rainfall had on Polder 32. Interestingly, the year that cyclone Aila resulted in the inundation of Polder 32 (2009) was not a wet year; in fact, the SPI indicates that it





Notes: Mongla is the closest BMD station to Polder 32. 1991 12 month SPI not available.

Figure 4.10. Monthly Mean Rainfall and 12 Month SPI, Mongla, 1991-2012

was a moderately dry year. It is not evident that precipitation during the 1991-2012 time period had a significant effect on land cover change. This finding is consistent with Islam, et al [2014]. A list of the largest natural disasters to occur in southern Bangladesh from 1986 to 2013 is given in Table 4.5.

Because of the dynamic nature of the polder and surrounding landscape, it is difficult to compare imagery with limited dates and draw definitive conclusions. Although there is no doubt that imagery collected at the right date would indicate effects on Polder 32 from these disasters, the temporal resolution of this collection of Landsat data is insufficient to make a visual correlation.

Table 4.5. Natural Disasters in Area of Southern Bangladesh since 1986

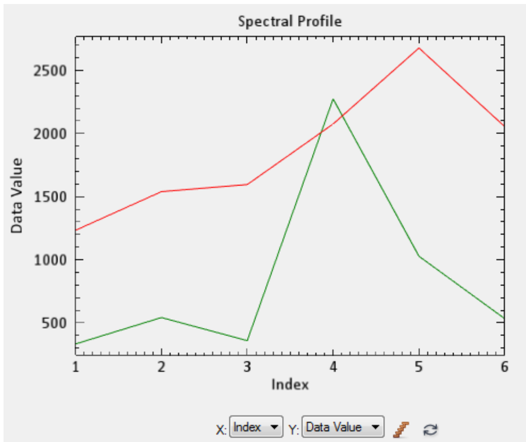
Year	Event	Impact
11/8-9/1986	cyclonic storm	90 km/hr winds at Khulna; 14 persons killed; significant damage to crops and infrastructure
1987	flood	
1988	flood	
11/24-30/1988	severe cyclonic storm	160 km/hr winds, 4.5 m storm surge in Mongla; massive damage to crops and infrastructure
11/24-30/1988	cyclone & storm surge	over 5,700 people killed , wildlife and livestock , crops damaged
4/29/1991	cyclone	
1994-1996	drought	most persistent drought in country recent history; significant damage to farmers, rice and jute crops
1998	flood	over 2/3 of country flooded; 5 SW districts bordering India flooded, leaving over 3 million people homeless
11/19-22/1998	cyclone	90 km/h winds, 1.2-2.4 m storm surge
2000	flood	
Nov. 15, 2007	Cyclone Sidr	over 3,000 deaths throughout country; Sundarbans damaged, thousands of wildlife and livestock died
May 25, 2009	Cyclone Aila	190 deaths; 7,000+ people with injuries; damage to 6,000 km of roads; more than 1,700 km of embankments collapsed; more than 500,000 homeless
May 16, 2013	Cyclone Mahasen	90 km/h winds ; 17 dead, 1.2 million people with losses and damage throughout country;

Notes: Sources: Hossain, et al. [2012] and UNICEF [2016].

4.3.2 Spectral Signatures & Surface Reflectance

An attempt was made to find Landsat spectral profiles for the five cover classes of interest, but profiles were surprisingly absent in the literature, as well as in the available USGS and NASA spectral libraries. Figure 4.11 illustrates the spectral signatures of single "pure pixels" of known land cover types from 2011 imagery for areas that have: a) grown rice only, b) only cultivated shrimp, c) have alternated seasons of growing rice and shrimp, and d) contain only mangroves. The "rice only" green season (2011312) profile has a sharp peak at band 4, and is very similar to the peak in the "alternating shrimp & rice" cover in the green season, as would be expected. The dry profile (2011040) for the "rice only" location exhibits a different profile than the "rice only" signature, peaking at band 5, possibly due to higher reflectance from adjacent bare soil or barren land. The dry profile for the "alternating shrimp/rice" cover type does not look like either rice or (presumed) adjacent dry soil/barren land. The profiles for the "shrimp only" cover plot look very similar to one another in shape for the green and dry season, peaking at both bands 2 and 4, with the dry season having higher reflectance. The "mangroves" profile is very similar to the green season "rice only" profile, but with a higher peak at band 4; the green season peak for mangroves is slightly greater than the dry season profile, supporting the observation that mangroves are evergreen. These plots indicate that, theoretically, the spectral signatures of the land cover classes of interest can be distinguished from one another, in both the green and dry seasons.

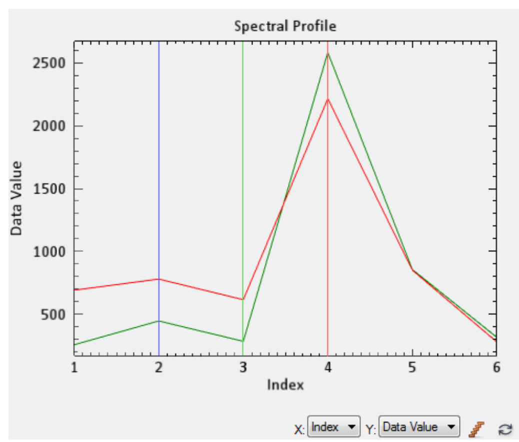
Figure 4.12 shows two plots of mean surface reflectance values for selected classes: one for the dry season images (for 3 dates: 1989075, 2009082, 2011040) for mangroves, rice/crops, and shrimp ponds; and one for the green season (for 7 dates: 1987358, 1988329, 1989315, 1991314, 1999352, 2008313, 2011312) for rice/crops and shrimp ponds. The plots are "stacks", so they are in order by date and by band, 1-5 & 7 (band 7 is noted as 6 in the plots). For example, in the dry plot, the first six bands on the x-axis correspond to 1989; bands 7 through 12 correspond to 2009, and bands 13 through 18 correspond to 2011. These plots differ from those in Figure 4.11 because they are means for many pixels of a given class, not just the value for one pixel.



a) Rice Only

b) Shrimp Pond Only

c) Alternating Shrimp (dry) & Rice (green)

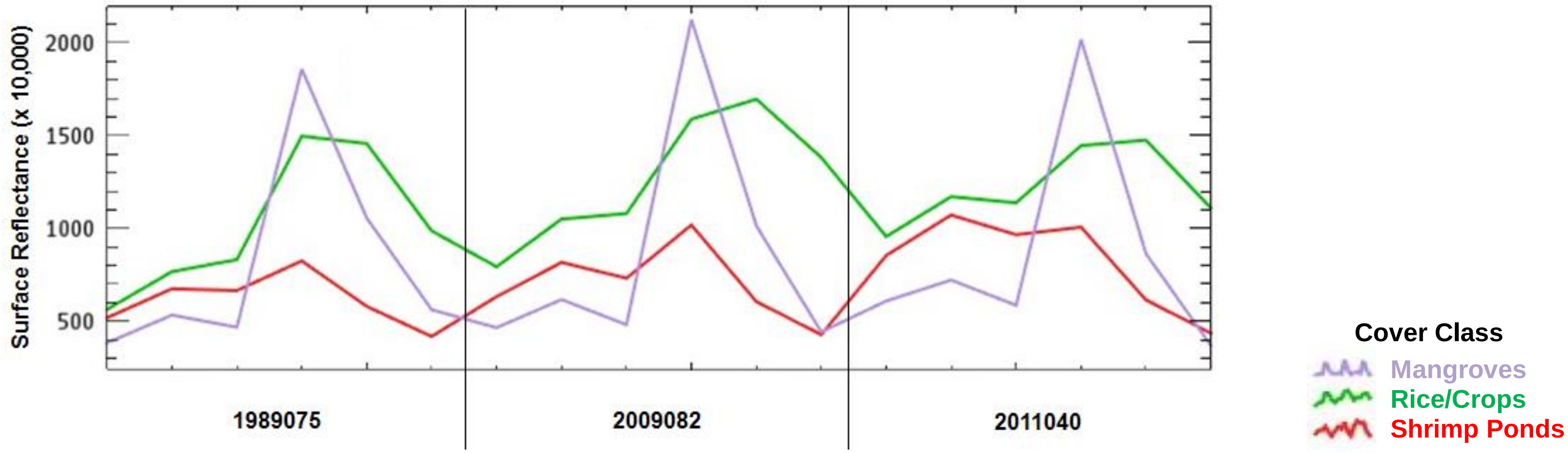


d) Mangroves

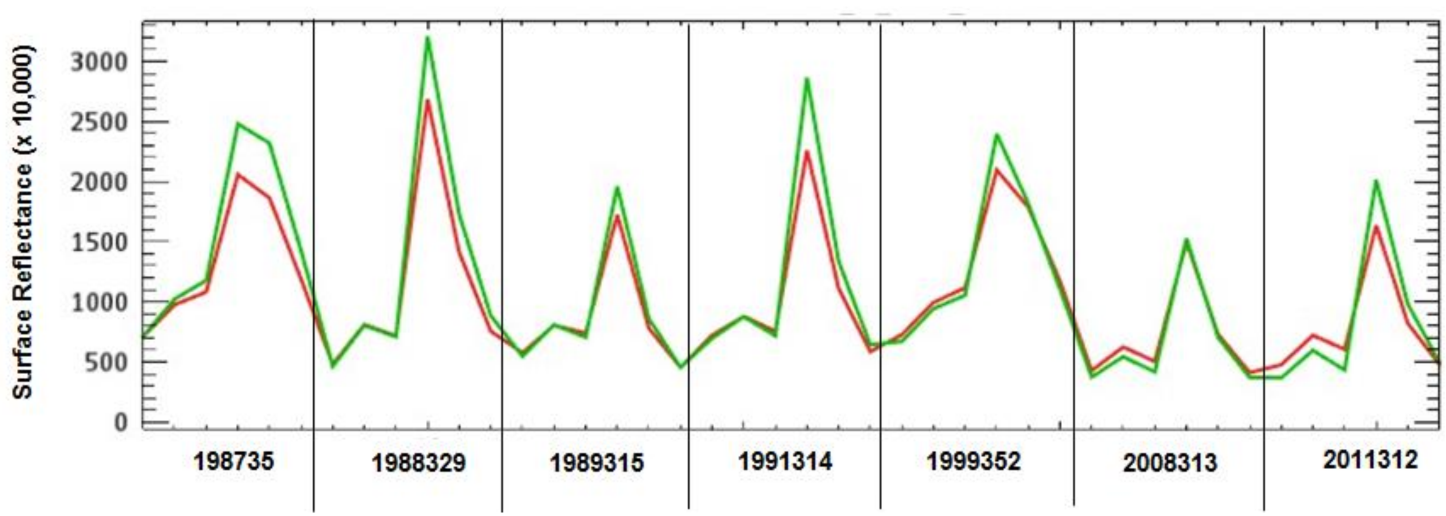
Notes: Outputs from ENVI. Data value (Y-axis) is surface reflectance (x 10,000); X-axis are bands 1-5 and 7 (7 is shown as 6 on plot). Red line is from 2011040 (dry season) image, green line from 2011312 (green season) image.

Figure 4.11. Spectral Plots of Surface Reflectance for Single Pixels for Known Classes in the Dry and Green Seasons, 2011

a) Dry Season



b) Green Season



Notes: X-axis= Bands 1-5& B7, by year; Y-axis=surface reflectance of class (x 10,000). Plots represent (a) 3 dry dates for the mangroves, rice/crops, and shrimp classes; and (b) 7 green dates for only rice/crops and shrimp classes.

Figure 4.12. Mean Surface Reflectance of Selected ROI Classes, 1987-2011

As shown for the green season plot (b), rice and shrimp/rice (in the green season), look almost identical, with rice/crop class always exhibiting slightly higher reflectances. In the dry dates plot (a), the class profiles are much more variable; mangroves always had the highest reflectances with a sharp peaks at band 4, followed by lower reflectance for rice/crops with broader peaks; shrimp ponds had the lowest reflectance, and an irregular pattern of peaks. Comparing the mean surface reflectance plots for rice/crops and shrimp ponds indicates that better results might be obtained from images from the dry season, rather than the green season, although the single pixel signatures imply very distinct patterns for both seasons.

4.3.3 Selection of ROI and Separability of Classes

The recommended number of training pixels of 10-100n (60-600), is satisfied for all of all of these classes. The following classes and pixel counts were used in the surface reflectance estimates, classification, and NDVI determinations:

- Water: 2,343 pixels
- Developed: 290 pixels
- Mangroves: 4,954
- Rice/Crops: 2,129
- Shrimp Ponds: 773

To determine how distinguishable the regions of interest for the land cover classes were from one another, separability of the classes derived from the green classification images were assessed using the Jeffries-Matusita statistic in ENVI (Appendix B). The range of values for the JM statistic is 0 to 2; well-separated values exceed 1.9. For the 1988329 image, the JM statistic for separability for two classes ranged from 0.744 to 1.99. The least separable pairs were rice/crops and shrimp ponds (0.744) and developed and shrimp ponds (0.807), indicating poor separability; all other pairs exceeded 1.26, indicating moderate separability. As a class, mangroves showed the best separability in the 1988329 image, with values of 1.994 and above all other classes.

The 2011312 image showed better separability overall compared to the 1988329 image. The JM statistic for separability for two classes ranged from 0.986 (for developed and shrimp ponds) to

2.00 (for mangroves and water). The other least separable pairs were rice/crops and shrimp ponds (0.987) indicating poor separability. Rice/crops and developed had a JM value of 1.72, indicating moderate separability. All other pairs of classes exceeded 1.90, indicating good separability. Like the 1988329 image, mangroves showed the best separability with values of 1.97 and above all other classes.

4.3.4 Classification and Change Detection

To ascertain whether season had an effect on classification, supervised classification using MLC was performed for two dates for images from the green and the dry seasons. The results for the green season (1988329 & 2011312) are shown in Table 4.6 and Figure 4.13; the results for the dry season (1989075 & 2009082) are shown in Table 4.7 and Figure 4.14. The extent of the study area that encompasses Polder 32 is 237.7 km^2. Based on the green season results, in 1988, the area of rice/crops was 81.40 km^2, and the area of shrimp ponds was 22.00 km^2; by 2011, this changed to 58.66 km^2 and 46.82 km^2, respectively. This estimate represents a 27.93 % decrease in rice/crops and a 112.81 % increase in shrimp ponds over 23 years, or an increase of about 5%/year in shrimp pond growth over the 23 years evaluated. Based on the dry season results, in 1989, the area of rice/crops was 66.56 km^2, and the area of shrimp ponds was 33.58 km^2; by 2009, this changed to 62.30 km^2 and 43.85 km^2, respectively. This estimate represents a 6.40 % decrease in rice/crops and a 30.58% increase in shrimp ponds, or an increase of about 1.3%/year in shrimp pond growth over the 20 years evaluated.

The dry season change detection results are about 4 times lower than the green season results for the rice/crops and shrimp pond class. The dry season figures indicate more developed area than in the green season. For both seasons, the area of mangroves in the Sundarbans is essentially; this is expected due to the protected status of the forest unchanged (although somewhat lower in the 2011312 analysis). Interestingly, in both the latter images (2009082 and 2011312), the small streams within the Sundarbans are erroneously identified as shrimp ponds. In addition, the dry season results indicate the presence of significantly more shrimp ponds off of Polder 32, on adjacent polders to the north and west, compared to green season results (Figures 4.13 and 4.14).

Table 4.6. Results of Supervised Maximum Likelihood Classification (Green Season)

	1988329		2011312		Percent Difference*	Area Difference (T2-T1)
Class	**Percent of Image (%)**	**km^2**	**Percent of Image (%)**	**km^2**	**(%)**	**km^2**
Water	17.92	42.58	20.12	47.82	+12.29	+5.23
Developed	14.15	33.64	12.61	29.97	-10.91	-3.67
Mangroves	24.43	58.08	20.90	54.43	-6.28	-3.65
Rice/Crops	34.25	81.40	24,68	58.66	-27.93	-22.74
Shrimp Ponds	9.26	22.00 (2,200 ha)	19.70	46.82 (4,682 ha)	+112.81	+24.82
TOTAL	100	237.7	100	237.7		

1 km^2 =100 ha
* % Difference = ((T2-T1)/T1)*100

Table 4.7. Results of Supervised Maximum Likelihood Classification (Dry Season)

	1989075		2009082		Percent Difference*	Area Difference (T2-T1)
Class	**Percent of Image (%)**	**km^2**	**Percent of Image (%)**	**km^2**	**(%)**	**km^2**
Water	17.67	42.00	18.28	43.46	+3.48	+1.46
Developed	16.04	38.12	13.20	31.38	-17.68	-6.74
Mangroves	24.17	57.44	23.86	56.71	-1.27	-0.73
Rice/Crops	28.00	66.56	26.21	62.30	-6.40	-4.26
Shrimp Ponds	14.13	33.58 (3,358 ha)	18.45	43.85 (4,385 ha)	+30.58	+10.27
TOTAL	100	237.7	100	237.7		

1 km^2 =100 ha
* % Difference = ((T2-T1)/T1)*100

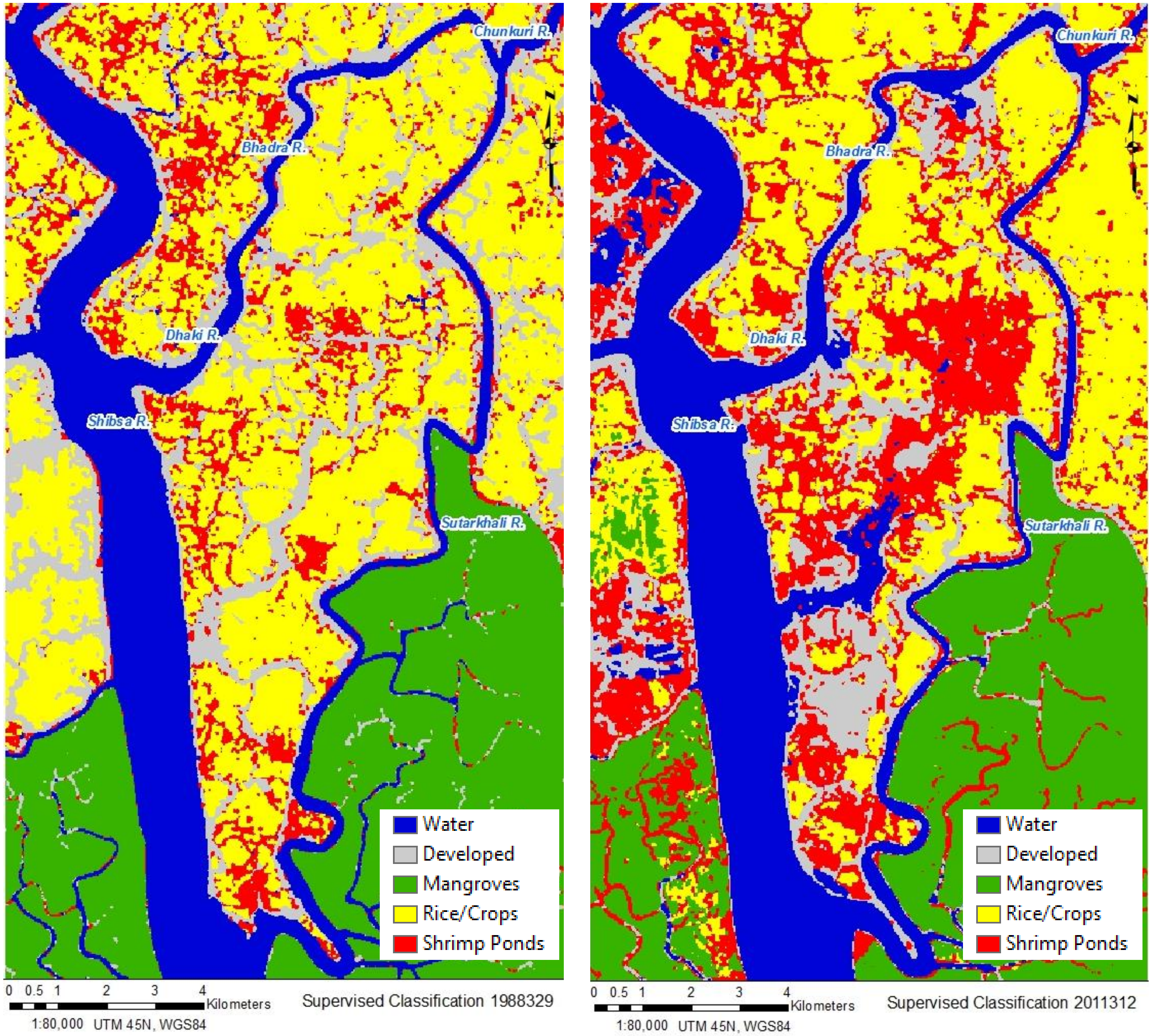


Figure 4.13. Supervised Classification Plots for the Green Season Images

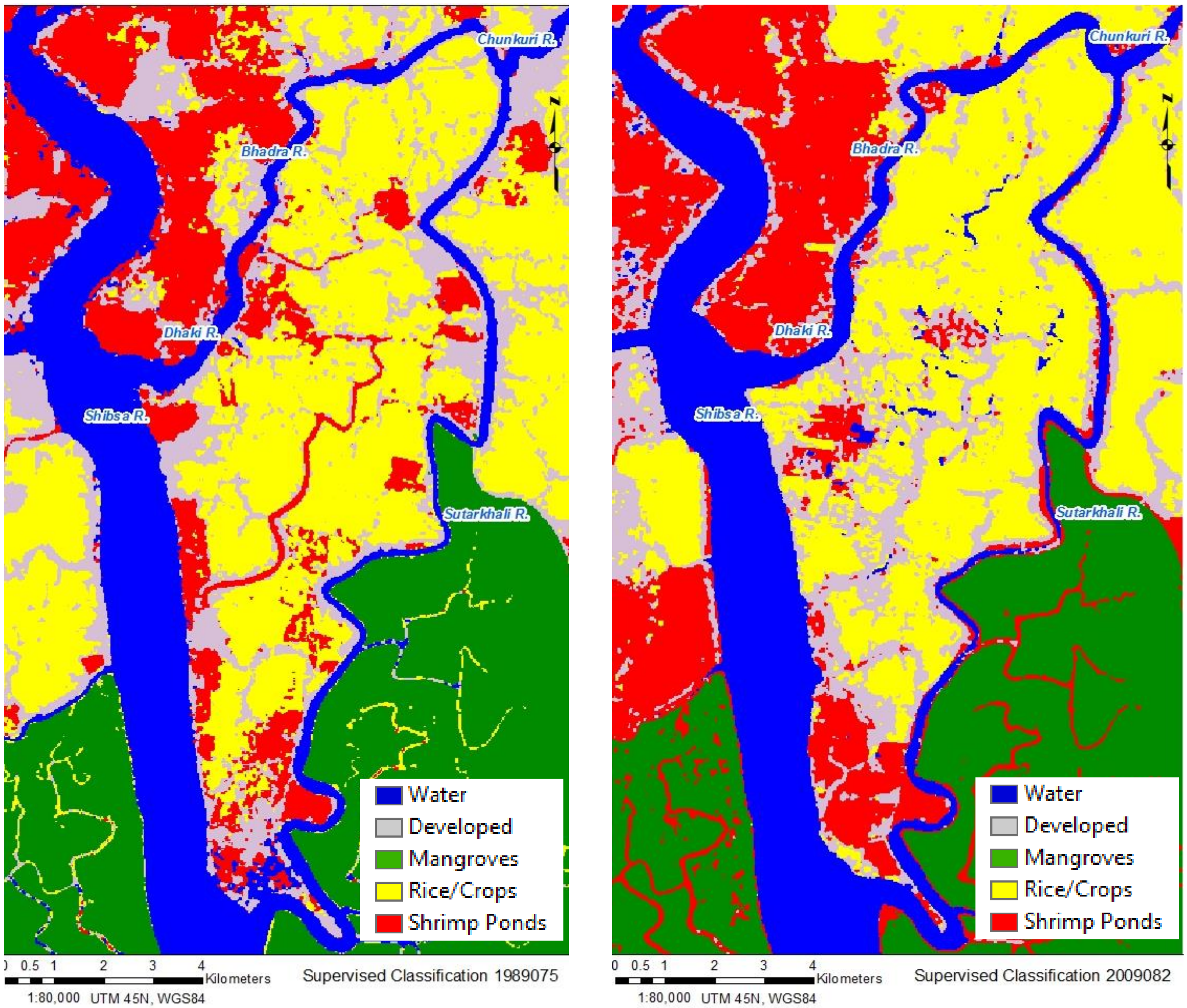


Figure 4.14. Supervised Classification Plots for the Dry Season Images

When interpreting the classification results, it should be recalled that the shrimp pond class actually includes all ponds present on Polder 32, so the estimates of area for shrimp ponds only is a portion of this estimate.

4.3.5 Accuracy Assessment

An accuracy assessment was performed using high-resolution imagery as reference data. The latter classification images for the green and dry seasons (2011312 and 2009082) were checked using a May 2012 Geoeye (dry season) high-resolution (0.5 m) image. No historical high-resolution imagery was available for the earlier dates, so no accuracy assessment was performed for the earlier dates. Unfortunately, this is a common issue with all remote sensing change detection methods. It is recognized that this results in a comparison with a dry season image against a green season image, and that the 2009082 image was taken before cyclone Aila, so the accuracy assessment should be viewed cautiously.

A set of 251 random pixel locations were generated using ENVI's post classification tools. To create the error matrix, the 251 random pixels were inspected in the 2012 Geoeye image to determine the "real" class, and the land cover type for each point was assigned to one of the classes used in the MLC; the same points in the classified images were coded in the same way. The results are compared in the form of a matrix; with the number correctly identified shown on the diagonal, in shaded boxes.

Table 4.8 shows the error matrix for the green season classified image (2011312). The overall accuracy was 78.1%. The producer's accuracy (of all the land in a certain category, such as mangrove, what fraction was correctly assigned in the image) ranged from 94.7% for mangroves to 51.9% for developed. The user's accuracy (of the pixels in the image assigned to a category, what fraction matched the actual land-use) ranged from 100% for mangroves to 35.6% for shrimp ponds. Given the range of accuracies for classes, the overall accuracy is no doubt skewed by the developed and shrimp pond class user's low accuracy results.

Table 4.9 shows the error matrix for the latter classified image for the dry season (2009082). The overall accuracy was 79.3%. The producer's accuracy ranged from 100% for mangroves to

Table 4.8. Error Matrix for Green Season Classified Image (2011312)

	Pixels Identified in Reference Image					
Classified	**Water**	**Developed**	**Mangroves**	**Rice/Crops**	**Shrimp Ponds**	**Total**
Water	**55**	0	0	2	0	57
Developed	5	**14**	0	6	2	27
Mangroves	0	0	**54**	0	0	54
Rice/Crops	1	6	1	**57**	3	68
Shrimp Ponds	3	7	2	17	**16**	45
Total	64	27	57	82	21	**251**
Producer's Accuracy (%)	**85.9**	**51.9**	**94.7**	**69.5**	**76.2**	**78.1 (Overall)**
User's Accuracy (%)	**96.5**	**51.9**	**100**	**83.8**	**35.6**	

Notes: Shaded boxes are correctly identified in classified image.

Table 4.9. Error Matrix for Dry Season Classified Image (2009082)

	Pixels Identified in Reference Image					
Classified	**Water**	**Developed**	**Mangroves**	**Rice/Crops**	**Shrimp Ponds**	**Total**
Water	**52**	0	0	0	0	52
Developed	6	**17**	0	9	2	34
Mangroves	1	0	**57**	0	0	58
Rice/Crops	3	3	0	**56**	2	64
Shrimp Ponds	2	7	0	17	**17**	43
Total	64	27	57	82	21	**251**
Producer's Accuracy(%)	**81.3**	**63.0**	**100**	**68.3**	**81.0**	**79.3 (Overall)**
User's Accuracy (%)	**100**	**50.0**	**98.3**	**87.5**	**39.5**	

Notes: Shaded boxes are correctly identified in classified image.

63% for developed. The user's accuracy ranged from 100 % for water to 39.5% for shrimp ponds.

Some interesting patterns emerge in comparing the green season and dry season accuracy results. The overall accuracies for the green season and dry season were essentially the same (78-79%). The producer's accuracies (correctly identified) for the green season were surprisingly similar to the dry season. The producer's accuracies were better for some classes for the green season, and better for others in the dry season. The producer's accuracy for the rice/crops class was slightly lower (68.3%) for the dry season than the green season (69.5%); the result for the shrimp ponds (81%) for the dry season was better than the green season (76.2%). The user's accuracy (misidentified) for the shrimp ponds was very low in both seasons: 35.6% for the green season, and 39.5% for the dry season. The user's accuracy for the rice/crops class was slightly lower (68.3%) for the dry season than the green season (69.5%); the result for the shrimp ponds (81%) for the dry season was better than the green season (76.2%). Water and mangroves were the most reliably identified classes in both seasons, greater than 97% in all cases, and shrimp ponds and developed were misidentified most often for both seasons. For both seasons, the shrimp ponds showed the biggest differences in the user's and producer's accuracies, with the user's accuracies being about half the value of the producer's accuracies. Based on the guidance of no less than 85% overall and 70% accuracy for any class, the results indicate an inadequate overall classification, and poor producer's and user's results for the developed, rice/crops, and shrimp pond classes. As mentioned previously, although the the green season accuracy assessment was based on a reference image taken within a time frame close to the classification image, the results should be viewed with caution since the reference image is from a dry season.

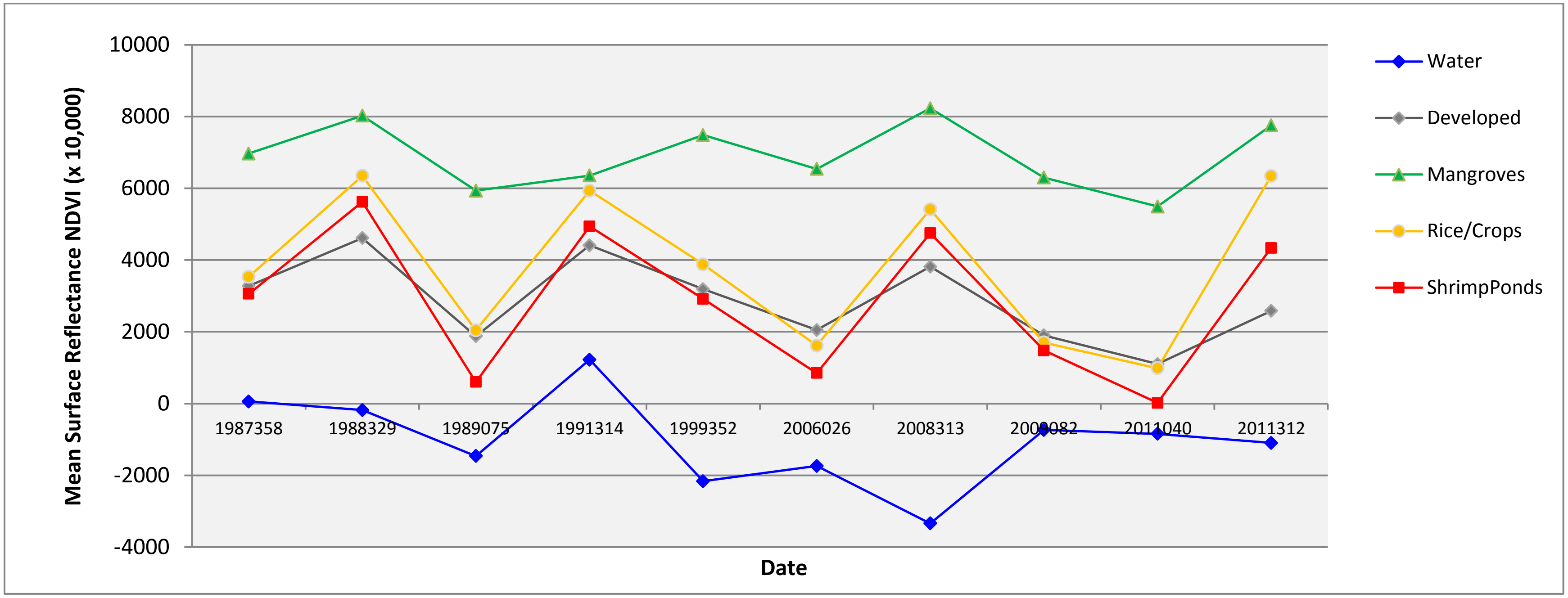
4.3.6 NDVI Surface Reflectance

Mean NDVI surface reflectance values (x 0.0001) for 1987-2011 are shown in Table 4.10 and Figure 4.15. As expected, water bodies generally exhibit a negative NDVI (except 1987358 and 1991314). The original data for the water class were checked, and the NDVIs calculated manually. The results were the same as shown in Table 4.10, so there is evidently a problem with the processing of the LEDAPS data. Mangroves consistently have the highest NDVI values of all classes; rice paddies track shrimp ponds; and developed areas show a similar pattern to rice/crops, although with lower values. Even though the developed class was intended to encompass the embankments and residential areas, it is highly likely that the NDVI values are from trees that tend to surround the embankments and residential areas, and are not able to be differentiated because the pixel size of the images. Rice paddies demonstrate a seasonal pattern, with higher mean NDVI values in the green season, and lower values in the dry season. Although rice paddies NDVI track shrimp ponds (shrimp ponds are rice in the green season), rice has a slightly higher mean NDVI than all shrimp ponds. The NDVI values for all dates were categorized into five ranges in ArcMap, and are shown in Figure 4.16.

Table 4.10. Results of NDVI Evaluation, 1987-2011

Mean NDVI Surface Reflectance (x 10,000) by Date and Class										
Date	**Water**	**sd**	**Devel.**	**sd**	**Mang.**	**sd**	**Rice/ Crops**	**sd**	**Shrimp Ponds**	**sd**
1987358	60[a]	1,969	3,278	952	6,969	311	3,536	616	3,058	985
1988329	-181	3,164	4,615	1,115	8,025	265	6,346	909	5,622	1,385
1989075	-1462	2,327	1,879	1,332	5,932	625	2,042	1,868	602	1,422
1991314	1,221[a]	1,971	4,410	1,064	6,356	336	5,935	662	4,940	1,064
1999352	-2,165	2,315	3,188	1,078	7,484	290	3,880	793	2,915	1,052
2006026	-1,738	1,286	2,049	1,083	6,540	294	1,615	844	849	1,396
2008313	-3,340	2,101	3,817	1,916	8,228	213	5,413	1,667	4751	1,906
2009082	-736	828	1,903	1,203	6,298	259	1,700	1,039	1,480	1,269
2011040	-841	575	1,105	831	5,491	318	986	1,116	19	1,090
2011312	-1,095	598	2,582	1,837	7,751	265	6,341	944	4,337	2,013

Notes: Values are surface reflectance NDVI x 10,000; sd= 1 standard deviation.
[a] *Likely an error in LEDAPS data; value should be negative.*



Notes: X-axis= by year, 1987-2011; Y-axis=mean NDVI surface reflectance of class (x 10,000). See Table 4.10 for data.

Figure 4.15. Mean NDVI Surface Reflectance by Land Cover Class, 1987-2011

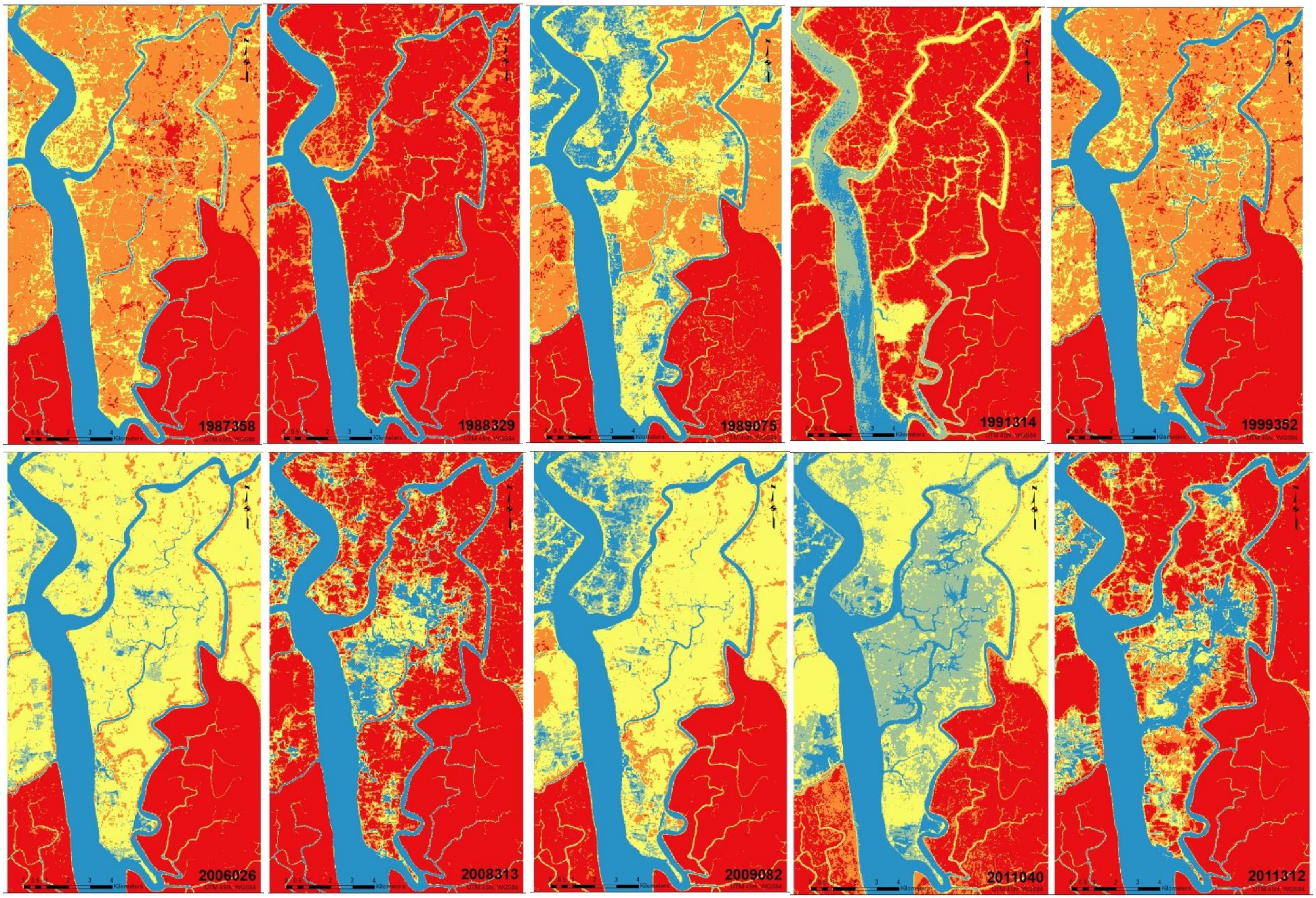
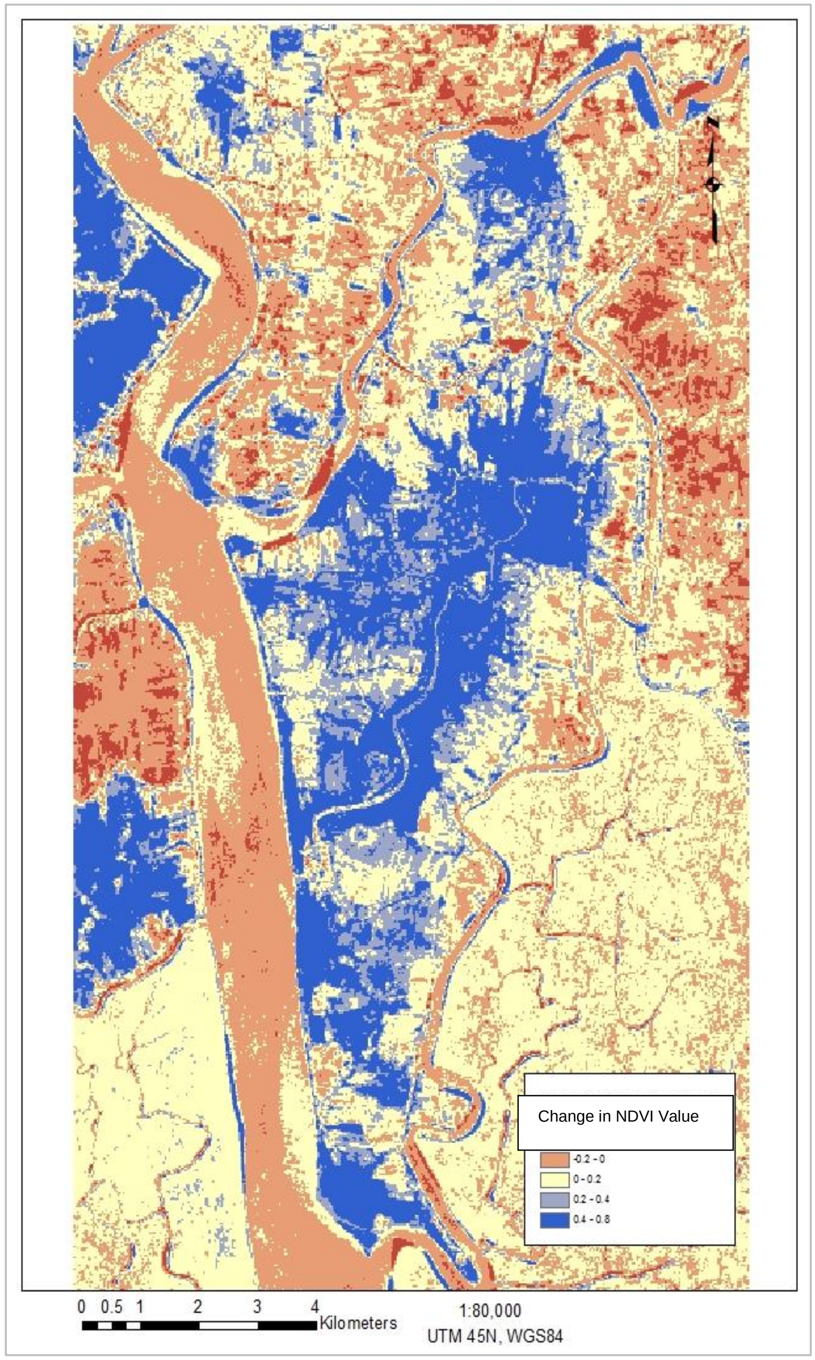


Figure 4.16. NDVI Surface Reflectance, 1987-2011

4.3.7 Green Season NDVI Image Difference

The data from the NDVI surface reflectance plots for two dates from the green season (1988329 and 2011312) were subtracted using band math in ENVI to create an NDVI difference image. In Figure 4.17, negative changes in NDVI values are shown in reds and pinks, and positive changes in NDVI values are in beige and shades of blue, with the highest positive difference shown in dark blue. As can be observed in Figure 4.17, the majority of Polder 32 shows significant NDVI changes over the 23 year time period. Other areas of significant change in NDVI can be noted in the adjacent polder to the west.

With shrimping, the landscape can look very different from one week or month to the next, depending on how the ponds are flooded. With rice, NDVI is very sensitive to the age and health of plants. Furthermore, because the 2011312 image was taken in 2011 after both cyclones Sidr and Aila, it is not possible to say what caused the changes observed in



Notes: Image created by subtracting NDVI values from Time 2 (2011312) by Time 1 (1988329).

Figure 4.17. Green Season Image Difference NDVI Surface Reflectance (1988329 & 2011312)

NDVI. Paddy fields on Polder 32 were covered with sand and waterlogged as late as 2011, which would greatly affect NDVI values. The Sundarbans, located to the south of Polder 32, show very little change in NDVI over time, as would be expected since the mangroves are essentially evergreen.

4.4 Discussion and Conclusions

4.4.1 Summary

The objective of this study was to ascertain if a simple method using remote sensing data could be used to quantify the conversion of rice paddy to shrimp farms in the area of Polder 32. Eleven cloud-free, geometrically-and atmospherically-corrected Landsat (LEDAPS) surface reflectance images were obtained. Patterns of change in reflectance were evident in the images, confirming that significant change had occurred in the area in the span of 24 years, especially adjacent to the western side of Polder 32. However, it is not possible to say with certainty whether the changes observed were as the result of rice/crop conversion to shrimp ponds, or from man-made or natural environmental impacts. Although the available imagery was not of sufficient temporal resolution to track all natural disasters, physical changes over time, including erosion of the shoreline and widening of adjacent rivers and inland streams, revealed the dynamic nature of the polder.

Spectral signatures for the classes in known locations were evaluated for wet and dry seasons. It was observed that rice spectral signatures for areas that seasonally alternated between shrimp pond and rice cultivation mimicked the signature of areas that cultivated rice only, but the shrimp signatures from the alternating cultivation areas did not look like areas that cultivated shrimp only. Moreover, there was more variability in the dry signatures of the cover classes than during the green season. Mangroves had a very consistent spectral signature during both dry and green seasons.

A supervised classification using the MLC was performed using ENVI software for two dates during the peak vegetative (green) season, and two for the dry season: A set of training samples for the classification were produced for five land cover classes: water; developed areas;

mangroves; rice/crops; and shrimp ponds. Separability tests were performed with pairs of classes to quantify how well the classes were distinguished from one another. Mangroves showed excellent separability with all classes; the least separable pairs were rice/crops and shrimp ponds, and developed and shrimp ponds; all other pairs of classes indicated good separability. Undoubtedly, variable soil moisture had an effect on the spectral signatures of several classes, although it was not quantified.

Following classification, post-classification change detection procedures were performed. Based on the green season (using the 1988329 and 2011312 images) results, a 27.9 % decrease in rice/crops and a 112.8 % increase in shrimp ponds was indicated, resulting in an increase of about 5%/year in shrimp ponds over the years evaluated. The dry season results (using the 1989075 and 2009082 images) showed a much lower level of change, about 4 times lower that the green season results: a 6.4 % decrease in rice/crops and a 30.58 % increase in shrimp ponds. The area of mangroves in the Sundarbans was essentially unchanged from 1988 to 2011. An error matrix was produced for the green and dry season latter classification images using reference points from a May 2012 high resolution Geoeye image. The overall accuracies for both seasons were similar: 79.7% for the green season, and 78.1% for the dry season (compared to guidance of 85%). Based on the guidance of no less than 70% accuracy for any class, the results indicate an inadequate overall classification, and the results should be used with caution for all the classes except water and mangroves.

Surface reflectance NDVI values were also evaluated in this study. As expected, water bodies exhibited a negative NDVI (with two noted errors); mangroves consistently have the highest NDVI values of all classes; and rice paddies track shrimp ponds. Rice paddies demonstrate a seasonal pattern, with higher mean NDVI values in the green season, and lower values in the dry season. Although rice paddies NDVI values track shrimp pond NDVIs (shrimp ponds are rice in the green season), rice has a slightly higher mean NDVI than all shrimp ponds. An NDVI difference image was also generated using two green season images (1988329 and 2011312).

4.4.2 Discussion and Conclusions

There are many studies of rice production on a regional scale using satellite imagery, but most have been conducted using sensors that have more bands (than Landsat 5's six bands), lower resolution (such as MODIS), and at a larger geographic scale than Polder 32. There is a paucity of information regarding the use of Landsat imagery for quantifying the conversion of rice paddies to shrimp in Southwest Bangladesh, and a lack of spectral signatures for these types of land covers. This research indicates that the reason for the lack of literature is not that conversion of rice to shrimp is not happening, but is likely because Landsat's 30 m spectral resolution is insufficient to distinguish changes in land cover in densely populated areas with small features such as ponds, houses and embankments. In principle, the 16 day return time of Landsat should provide excellent temporal coverage for observing the constantly changing landscape, but cloud cover, especially during the rainy monsoon season, makes the vast majority of images unusable. Although the temporal resolution of Landsat imagery does not allow for the tracking of natural disasters, there is sufficient detail to observe changes in physical features such as increases in channel width and erosion of shorelines.

The findings of this study imply that the current method of imagery evaluation can serve to evaluate land cover change over time at smaller spatial scales, but this method is better for suited some land cover classes than others. Rice paddies and shrimp ponds were found to have distinct and measureable spectral signatures, and mangroves in the Sundarbans were consistently and easily differentiated from all other land cover classes. However, based on the guidance of 85% overall classification accuracy, and no less than 70% accuracy for any class, the results of this study indicate that the method as described produces an inadequate overall classification, and specifically, poor results for the rice/crops, shrimp pond, and developed cover classes. The shrimp pond class included all ponds, so the classification results overestimate shrimp ponds. Nonetheless, it is reasonable to assume that an increase in "shrimp pond" area is due to increases in shrimp ponds, and not fresh ponds. Therefore, measurements of long-term change provide meaningful information about growth in shrimp pond area, albeit with the large uncertainties due to low classification accuracy.

Patterns of change were clearly observed in the review of 24 years of Landsat imagery, but it is difficult to say what the cause(s) of those changes were. In the three years in which fieldwork was conducted at Polder 32 (2012-2014), the polder appeared to be in a constant state of flux. In a matter of months, new dwellings and other structures were constructed; embankments were destroyed and recreated; some land become water-logged while other areas dried out; rice paddies were converted into shrimp ponds in some areas, while other communities decided to expand the types of crops cultivated and banish shrimp farms altogether. This underlying dynamic made the evaluation of a longer-term temporal change detection analysis of questionable utility. Furthermore, the concept of "reference points" used to geometrically correct imagery, and to verify estimates are virtually meaningless in such a constantly changing environment.

Compared to other estimates of the amount of land that has been converted from agriculture to shrimp farms in southwest Bangladesh, this method appears to underestimate the changed area [Datta, 2010; Hasan, et al., 2013; Islam, et al., 2015]. For example, Datta et al. [2010] estimated that shrimp ponds in the southwest had increased at a rate of 20%/year from 1983 to 1997. By comparison, this method resulted in an increase of 5%/year in the green season, and significantly less in the dry season. However, if Dacope upazila (which has over 700 mauzas) was estimated to have over 10,000 ha of *Bagda* shrimp ponds in 2003, the current estimate for the green season for just Polder 32 (which has 6 mauzas) of 4,682 ha of shrimp ponds in 2011 seems comparable. It is possible that others' methods overestimated the results.

4.4.3 Limitations

There are several limitations in this study:

- The spatial resolution of Landsat (30 m) may preclude distinguishing the land cover classes of interest. For example, even though the developed class was intended to encompass the embankments and residential areas, it is highly likely that the results reflect the presence of trees and other vegetation that tend to surround the embankments and residential areas. Some inland waters were less wide than 1 pixel.

- The dynamic nature of Polder 32 makes it difficult to ascertain which changes that occurred can be attributed to which environmental phenomena, natural or man-made.

- The tidal stage of the imagery has a significant bearing on its interpretation. Imagery taken at high tide could be mistaken for embankment failure, tidal surge or flooding impacts.

- Only five cover types were evaluated; in reality, there are many more, so this analysis likely simplifies the physical landscape.

- It is difficult to separate out the potential effects of natural disasters on rice crop reduction from shrimp pond conversion. In particular, cyclone Aila in 2009 had a devastating impact on Polder 32, and some of the impacts could be misinterpreted as conversion from rice paddy to shrimp farming.

- Although it cannot be quantified, there could be an effect on the rice/crops change detection results due to increased productivity of rice varieties over the same time.

- With this type of classification, there is always the issue of "mixed pixels", where one category of land cover type must be assigned to a pixel that may actually be comprised of several different categories.

- The use of the class "shrimp ponds" does not distinguish between other types of "wet classes," such as wetlands, ponds for fish cultivation, or ponds used for drinking and bathing, so it overestimates the area of that land cover class.

- There were no field-based reference samples (only those based on Geoeye imagery), and the accuracy assessment only utilized 251 samples. Use of more points, or field-derived ground-truth points may have increased the accuracy of the classification. There were insufficient field locations of known classes to use in the accuracy assessment; those that were known were used to select ROIs. Guidance recommends against using same locations for ROIs and reference locations.

- The accuracy assessment is limited. It usually very difficult to find historical reference images, and high-resolution satellite imagery and aerial photography are not often available for remote areas. In addition, the reference imagery that was used was not collected during the same year as the Landsat imagery.

- There are obvious errors in the NDVI values for the pre-processed LEDAPS data make the data set questionable. As noted by Huang, et al. [2009], these data were not always reliable.

- There is a lack of reference data (such as a national land use map) to verify estimates of change.

- There is uncertainty in other's estimates of rice and shrimp cultivation, making a comparison difficult.

- The method does not distinguish changes that could occur purely by chance.

The findings of this study imply that the current method of imagery evaluation can serve to as a first step to evaluate land cover change over time at smaller spatial scales, and may be refined to improve results, and the method is better for suited some land cover classes than others.

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CHAPTER 5

Summary

5.1 Research Contributions

Human-water systems are extremely complex; many factors affect water security, regardless of the scale being assessed, and an integrated approach is necessary. The goal of this research was to provide insight into which factors contribute to drinking water security in rural Bangladesh using an interdisciplinary approach, and to contribute to the understanding of how the analysis of drinking water security is affected by scale. This was accomplished by a multi-scalar approach, using both "top down" and "bottom up" methods. "Top down" methods included the analysis of water indices at a national level, and the use of remote sensing to evaluate land cover change. A "bottom up" interdisciplinary approach was used to assess local water security in a coastal Bangladesh community by evaluating residents' access to drinking water, and by conducting site-specific water quality social surveys.

National level water security was evaluated by comparing hydro-social parameters for Bangladesh and the more water-secure Sri Lanka. Research findings described in Chapter 2 indicate that both Bangladesh and Sri Lanka's water security is affected by their monsoon climate, and the spatial and temporal variability of rainfall. Sri Lanka appears to be more water secure than Bangladesh because it has a greater "soft capacity"- sufficient political and financial resources to compensate for its fewer physical water resources. This task revealed that water index comparisons offered limited insights on a small geographic scale, and study of the parameters themselves was found to be more meaningful than application of any one index. Regardless of the shortcomings, water indices were found to be a valuable tool to provide an overview of national water security, and to provide a means to integrate a variety of physical and social factors influencing human-water systems.

The water quality and access task described in Chapter 3 demonstrated that aggregation of drinking water data on a national scale masks local water security differences. Despite claims of achieving the MDG on a national level, the security and sustainability of drinking water supplies in coastal south-west Bangladesh is clearly threatened. Both groundwater and surface water drinking sources were observed to have levels of arsenic, salinity, and a multitude of other contaminants significantly above Bangladesh's drinking water criteria. This task also demonstrated that assessing social conditions is critical to understanding water security at a local level, and for effective resource management. Despite their resiliency, residents of Polder 32 and the region are faced with water insecurity, and their health and livelihoods continue to suffer.

The findings summarized in Chapter 4 indicate that Landsat imagery can be used cost-effectively to evaluate land cover change over time at smaller spatial scales, but that this method is better for suited some land cover classes than others. Rice paddies and and shrimp ponds were found to have distinct and measureable spectral signatures, but were difficult to distinguish from one another compared to mangroves and water. Mangroves in the Sundarbans were consistently and easily differentiated from all other land cover classes using Landsat 5 data. Estimates of increased aquaculture and decreased paddy farming using these methods indicated less change than has been reported in other studies. Because of spatial resolution and temporal limitations of Landsat data, changes can be observed, but it is difficult to determine what the observed changes signify. Despite these limitations, remote sensing may be a useful tool for identifying promising locations for more detailed studies on the ground.

5.2 Potential Future Work

The research presented here can provide a useful framework to assess water security in other parts of Bangladesh and the world, at a variety of geographic scales. The "top down" methods could be used to screen larger regions for the more labor-intensive and expensive "bottom up" work associated with on-the-ground tasks that are necessary for effective hydro-social research.

Other avenues of research could build on the current work to yield meaningful results. The role of rainfall variability and the onset of the monsoon in local water security should be further investigated. The integration of climate change impacts and environmental vulnerability in the context of water security needs to further studied. Research is needed to identify additional metrics regarding governance so that aspect of water security analysis can be improved.

Water quality and access should be evaluated at a regional scale in south-west Bangladesh to determine the extent of the salinity problem. Much could be gained by conducting integrated hydro-social surveys within local coastal communities who appear to be more water secure than others to determine what factors have contributed to their success. Remote sensing presents a variety of opportunities to explore the complexities of land cover change. Imagery from other sensors could be explored, such as the Indian IRS sensors, SPOT, MODIS, or various RADAR sensors (which are not sensitive to cloud cover). Data from the Landsat 8 sensor data could be used for higher resolution, but would not be useful to historical assessments, as it only came into existence as of February 2013. Other types of supervised classifiers, such as minimum distance, neural net, or parallelepiped could be applied to the same Landsat imagery used in this study. Research on other classification and transformation methods, such as random forest, decision tree, or PCA, could be performed in an attempt to improve the accuracy over the MLC supervised classification approach. Other indices besides NDVI could be evaluated, particularly those that are more sensitive to vegetation and standing water.

It is regrettable and ironic that the historical movement in coastal Bangladesh to convert agricultural land to aquaculture intended to address future food security for the nation's ever-growing population; instead, it has reduced the availability and suitability of cropland for subsistence farmers in many areas, and has contributed to their poverty and water insecurity. More research is needed to help develop solutions for the currently unsustainable water management practices in coastal Bangladesh so that residents have hope for future water and food security. As human and economic development continues to pressure diminishing water resources, the need for knowledge of concepts, methods, and tools will only increase, and the integration of physical and social data, as well as the collaboration of physical and social scientists is critical.

APPENDIX A

Rainfall Data for Mongla BMD Station, 1991-2012

ID	Station ID	Year	Mon	Rainfall (mm)	Max	Min	Mean
12021	41958	1991	1	29	24.61935	14.00968	19.3145161
12022	41958	1991	2	29	29.41786	18.17143	23.7946429
12025	41958	1991	3	20	33.47097	23.08387	28.2774194
12026	41958	1991	4	88	34.32333	25.36667	29.845
12027	41958	1991	5	91	33.80645	26.90968	30.3580645
12028	41958	1991	6	419	32.34667	26.09	29.2183333
12029	41958	1991	7	395	31.92903	26.42903	29.1790323
12030	41958	1991	8	298	31.94194	26.38065	29.1612903
12031	41958	1991	9	323	32.27667	25.67667	28.9766667
12032	41958	1991	10	259	31.37742	23.93871	27.6580645
12023	41958	1991	11	4	28.53333	18.96	23.7466667
12024	41958	1991	12	2	25.85161	15.51613	20.683871
12033	41958	1992	1	8	24.66774	13.63548	19.1516129
12034	41958	1992	2	108	26.55862	17.19655	21.8775862
12037	41958	1992	3	0	32.59032	22.77742	27.683871
12038	41958	1992	4	4	35.93333	25.00333	30.4683333
12039	41958	1992	5	118	34.02333	24.71	29.3666667
12040	41958	1992	6	174	33.68667	26.4	30.0433333
12041	41958	1992	7	350	31.26452	25.94194	28.6032258
12042	41958	1992	8	243	31.52581	26.25806	28.8919355
12043	41958	1992	9	170	31.28	26.04667	28.6633333
12044	41958	1992	10	55	31.34839	24.58387	27.966129
12035	41958	1992	11	2	28.91	20.40667	24.6583333
12036	41958	1992	12	0	26.11935	14.59355	20.3564516
12045	41958	1993	1	9	25.51935	14.06774	19.7935484
12046	41958	1993	2	21	29.04286	17.85357	23.4482143
12049	41958	1993	3	167	31.23226	20.38065	25.8064516
12050	41958	1993	4	72	33.95333	23.83333	28.8933333
12051	41958	1993	5	186	33.40645	25.10323	29.2548387
12052	41958	1993	6	424	32.24333	26.08	29.1616667
12053	41958	1993	7	225	31.85806	26.6129	29.2354839
12054	41958	1993	8	379	31.21935	26.41613	28.8177419
12055	41958	1993	9	243	30.85333	25.33	28.0916667
12056	41958	1993	10	91	32.1	24.68065	28.3903226
12047	41958	1993	11	36	29.55	20.45	25
12048	41958	1993	12	0	26.98065	16.13548	21.5580645
12057	41958	1994	1	4	26.18065	14.64839	20.4145161

12058	41958	1994	2	18	27.25357	16.64643	21.95
12061	41958	1994	3	40	33.07097	22.55161	27.8112903
12062	41958	1994	4	149	34.00667	24.21	29.1083333
12063	41958	1994	5	139	34.54516	25.99355	30.2693548
12064	41958	1994	6	344	31.55667	26.66	29.1083333
12065	41958	1994	7	278	31.69032	26.37742	29.033871
12066	41958	1994	8	380	31.2129	26.18387	28.6983871
12067	41958	1994	9	123	32.13667	26.01	29.0733333
12068	41958	1994	10	130	31.7129	24.29355	28.0032258
12059	41958	1994	11	3	28.74	20.46	24.6
12060	41958	1994	12	0	26.87742	15.07742	20.9774194
12069	41958	1995	1	4	24.50323	13.0871	18.7951613
12070	41958	1995	2	70	28.30357	16.68214	22.4928571
12073	41958	1995	3	11	33.02258	21.55806	27.2903226
12074	41958	1995	4	9	36.56667	25.74667	31.1566667
12075	41958	1995	5	208	34.81613	27.08065	30.9483871
12076	41958	1995	6	304	32.41333	27.13667	29.775
12077	41958	1995	7	244	31.95161	26.34194	29.1467742
12078	41958	1995	8	268	31.75484	26.60645	29.1806452
12079	41958	1995	9	302	31.37	26.11667	28.7433333
12080	41958	1995	10	148	31.34	24.72	28.03
12071	41958	1995	11	229	27.98333	20.78	24.3816667
12072	41958	1995	12	0	26.62333	15.69333	21.1583333
12081	41958	1996	1	2	25.39677	14.81613	20.1064516
12082	41958	1996	2	22	28.82143	16.83929	22.8303571
12085	41958	1996	3	24	33.55161	23.36774	28.4596774
12086	41958	1996	4	47	34.54	24.77	29.655
12087	41958	1996	5	119	35.39355	26.34194	30.8677419
12088	41958	1996	6	453	32.12667	25.82	28.9733333
12089	41958	1996	7	386	32.03226	26.40968	29.2209677
12090	41958	1996	8	357	30.40968	25.92258	28.166129
12091	41958	1996	9	133	32.74333	26.40667	29.575
12092	41958	1996	10	274	31.29032	24.16452	27.7274194
12083	41958	1996	11	1	29.45333	20.03	24.7416667
12084	41958	1996	12	0	26.26129	15.72581	20.9935484
12093	41958	1997	1	2	25.13548	13.67419	19.4048387
12094	41958	1997	2	70	27.41429	16.97857	22.1964286
12097	41958	1997	3	123	32.63548	22.45806	27.5467742
12098	41958	1997	4	131	32.11	22.20333	27.1566667
12099	41958	1997	5	214	34.22903	25.07742	29.6532258
12100	41958	1997	6	233	33.68	26.01333	29.8466667

12101	41958	1997	7	478	31.37097	26.04194	28.7064516
12102	41958	1997	8	355	31.76452	26.3871	29.0758065
12103	41958	1997	9	591	31.43333	25.48333	28.4583333
12104	41958	1997	10	12	31.43548	23.52581	27.4806452
12095	41958	1997	11	0	30.53333	21.2	25.8666667
12096	41958	1997	12	14	25.00323	15.56774	20.2854839
12105	41958	1998	1	29	23.32581	13.66452	18.4951613
12106	41958	1998	2	65	28.21786	17.73929	22.9785714
12109	41958	1998	3	149	30.35484	20.35484	25.3548387
12110	41958	1998	4	97	33.66333	23.99667	28.83
12111	41958	1998	5	234	34.33871	26.42581	30.3822581
12112	41958	1998	6	229	34.14333	27.77667	30.96
12113	41958	1998	7	294	32.35806	26.68065	29.5193548
12114	41958	1998	8	443	31.71935	26.52903	29.1241936
12115	41958	1998	9	553	31.94667	26.09	29.0183333
12116	41958	1998	10	110	32.33548	25.84194	29.0887097
12107	41958	1998	11	207	30.00667	22.27	26.1383333
12108	41958	1998	12	0	27.34194	16.55806	21.95
12117	41958	1999	1	1	26.18387	14.12258	20.1532258
12118	41958	1999	2	0	30.36786	17.87143	24.1196429
12121	41958	1999	3	0	34.36452	22.58387	28.4741936
12122	41958	1999	4	25	35.78966	26.14828	30.9689655
12123	41958	1999	5	202	33.64667	25.71	29.6783333
12124	41958	1999	6	262	32.44667	26.36	29.4033333
12125	41958	1999	7	435	31.63548	26.02258	28.8290323
12126	41958	1999	8	442	31.22258	26.09355	28.6580645
12127	41958	1999	9	479	30.81	25.83	28.32
12128	41958	1999	10	321	30.8129	24.86452	27.8387097
12119	41958	1999	11	12	29.66667	20.29	24.9783333
12120	41958	1999	12	0	27.35484	16.47419	21.9145161
12129	41958	2000	1	28	26.21613	14.43548	20.3258065
12130	41958	2000	2	9	27.20345	17.24828	22.2258621
12133	41958	2000	3	15	32.50323	21.96774	27.2354839
12134	41958	2000	4	134	34.49333	24.67	29.5816667
12135	41958	2000	5	283	33.66452	25.74194	29.7032258
12136	41958	2000	6	309	32.62	26.40667	29.5133333
12137	41958	2000	7	356	31.62581	26.13548	28.8806452
12138	41958	2000	8	209	32.42581	26.66129	29.5435484
12139	41958	2000	9	327	32.06333	25.72667	28.895
12140	41958	2000	10	124	31.67419	24.97419	28.3241936
12131	41958	2000	11	5	30.20667	20.81333	25.51

12132	41958	2000	12	0	26.98387	15.19032	21.0870968
12141	41958	2001	1	1	25.40968	13.11935	19.2645161
12142	41958	2001	2	19	29.83929	17.66429	23.7517857
12145	41958	2001	3	6	33.6	21.62581	27.6129032
12146	41958	2001	4	22	35.61667	25.49	30.5533333
12147	41958	2001	5	301	33.51613	25.27742	29.3967742
12148	41958	2001	6	539	31.09667	25.99	28.5433333
12149	41958	2001	7	445	31.34839	26.26129	28.8048387
12150	41958	2001	8	136	32.44839	27.1	29.7741936
12151	41958	2001	9	181	32.55333	26.02333	29.2883333
12152	41958	2001	10	251	31.92903	25.13226	28.5306452
12143	41958	2001	11	53	29.34667	21.74333	25.545
12144	41958	2001	12	0	27.03226	15.27097	21.1516129
12153	41958	2002	1	13	26.45161	14.93226	20.6919355
12154	41958	2002	2	5	29.66429	16.79286	23.2285714
12157	41958	2002	3	32	33.70645	21.92903	27.8177419
12158	41958	2002	4	74	33.41667	24.16667	28.7916667
12159	41958	2002	5	206	34.75806	25.93871	30.3483871
12160	41958	2002	6	983	32.93667	25.95333	29.445
12161	41958	2002	7	389	33.53226	26.87419	30.2032258
12162	41958	2002	8	441	31.73226	26.13548	28.933871
12163	41958	2002	9	492	32.44333	25.73333	29.0883333
12164	41958	2002	10	62	31.84516	24.00645	27.9258065
12155	41958	2002	11	89	29.54	20.58667	25.0633333
12156	41958	2002	12	0	27.04516	16.25161	21.6483871
12165	41958	2003	1	0	24.0129	12.20645	18.1096774
12166	41958	2003	2	2	29.43571	17.78214	23.6089286
12169	41958	2003	3	175	31.27419	20.66452	25.9693548
12170	41958	2003	4	41	34.70667	25.61333	30.16
12171	41958	2003	5	127	35.29355	26.1871	30.7403226
12172	41958	2003	6	351	32.67	26.44667	29.5583333
12173	41958	2003	7	284	32.7	26.74839	29.7241936
12174	41958	2003	8	229	32.67097	26.67419	29.6725807
12175	41958	2003	9	188	32.68	26.25333	29.4666667
12176	41958	2003	10	263	32.17742	25.19677	28.6870968
12167	41958	2003	11	0	29.99	20.05	25.02
12168	41958	2003	12	28	25.93226	15.90968	20.9209677
12177	41958	2004	1	0	24.44839	14.0129	19.2306452
12178	41958	2004	2	0	29.14138	16.57586	22.8586207
12181	41958	2004	3	7	33.46452	22.39677	27.9306452
12182	41958	2004	4	95	34.19	24.92333	29.5566667

12183	41958	2004	5	109	35.61613	26.39677	31.0064516
12184	41958	2004	6	293	32.95667	26.12	29.5383333
12185	41958	2004	7	280	31.9	26	28.95
12186	41958	2004	8	336	31.78387	26.23548	29.0096774
12187	41958	2004	9	506	31.91	25.97333	28.9416667
12188	41958	2004	10	274	31.47742	23.89032	27.683871
12179	41958	2004	11	3	29.67667	19.38	24.5283333
12180	41958	2004	12	0	27.45161	16.71613	22.083871
12189	41958	2005	1	28	25.64194	14.51935	20.0806452
12190	41958	2005	2	0	30.53929	18.22857	24.3839286
12193	41958	2005	3	93	33.10645	22.8	27.9532258
12194	41958	2005	4	25	35.78	25.34667	30.5633333
12195	41958	2005	5	238	35.3129	25.77742	30.5451613
12196	41958	2005	6	342	34.52333	27.41	30.9666667
12197	41958	2005	7	633	31.65484	26.13226	28.8935484
12198	41958	2005	8	264	32.15484	26.47742	29.316129
12199	41958	2005	9	391	32.33667	26.07667	29.2066667
12200	41958	2005	10	390	30.97097	24.83871	27.9048387
12191	41958	2005	11	1	29.25333	19.53333	24.3933333
12192	41958	2005	12	1	26.95806	15.88387	21.4209677
12201	41958	2006	1	0	26.63226	13.78065	20.2064516
12202	41958	2006	2	0	32.30357	19.36071	25.8321429
12205	41958	2006	3	14	33.80968	22.33871	28.0741936
12206	41958	2006	4	9	35.65333	25.51	30.5816667
12207	41958	2006	5	243	34.79032	26.06129	30.4258065
12208	41958	2006	6	255	33.15667	26.90667	30.0316667
12209	41958	2006	7	462	31.06452	26.14516	28.6048387
12210	41958	2006	8	318	31.40968	26.14839	28.7790323
12211	41958	2006	9	390	32.02	25.88333	28.9516667
12212	41958	2006	10	48	32.59677	24.69032	28.6435484
12203	41958	2006	11	6	29.67333	20.73333	25.2033333
12204	41958	2006	12	0	27.24194	15.91613	21.5790323
12213	41958	2007	1	2	25.44839	13.13871	19.2935484
12214	41958	2007	2	71	27.89286	17.7	22.7964286
12217	41958	2007	3	1	32.06452	20.45161	26.2580645
12218	41958	2007	4	64	34.54667	24.64667	29.5966667
12219	41958	2007	5	57	34.74194	26.2871	30.5145161
12220	41958	2007	6	226	33.08333	26.65333	29.8683333
12221	41958	2007	7	580	31.50323	26.17419	28.8387097
12222	41958	2007	8	262	32.26129	26.49032	29.3758065
12223	41958	2007	9	355	31.29	26.08333	28.6866667

12224	41958	2007	10	267	31.68387	23.85161	27.7677419
12215	41958	2007	11	101	29.4	20.98	25.19
12216	41958	2007	12	0	26	15.33871	20.6693548
12225	41958	2008	1	50	25.50323	14.42903	19.966129
12226	41958	2008	2	36	26.92414	15.59655	21.2603448
12229	41958	2008	3	12	32.83548	22.57097	27.7032258
12230	41958	2008	4	7	35.31667	24.88333	30.1
12231	41958	2008	5	146	35.65806	25.81613	30.7370968
12232	41958	2008	6	252	31.84667	26.12	28.9833333
12233	41958	2008	7	474	31.23871	25.93226	28.5854839
12234	41958	2008	8	217	31.83871	26.36129	29.1
12235	41958	2008	9	299	32.15333	26	29.0766667
12236	41958	2008	10	197	31.67097	23.9129	27.7919355
12227	41958	2008	11	0	29.65667	20.11667	24.8866667
12228	41958	2008	12	0	26.43226	17.04194	21.7370968
12237	41958	2009	1	0	26.57419	15.70645	21.1403226
12238	41958	2009	2	1	30.15714	17.53929	23.8482143
12241	41958	2009	3	10	33.59677	21.82581	27.7112903
12242	41958	2009	4	21	36.57	25.87	31.22
12243	41958	2009	5	219	34.84516	25.95806	30.4016129
12244	41958	2009	6	169	34.27	27.12333	30.6966667
12245	41958	2009	7	405	31.5871	26.31613	28.9516129
12246	41958	2009	8	477	32.39355	26.33226	29.3629032
12247	41958	2009	9	316	32.36333	26.21667	29.29
12248	41958	2009	10	96	32.03226	23.80968	27.9209677
12239	41958	2009	11	6	30.38667	20.52	25.4533333
12240	41958	2009	12	0	26.44194	15.05161	20.7467742
12249	41958	2010	1	0	24.36774	12.49677	18.4322581
12250	41958	2010	2	0	29.77143	17.08214	23.4267857
12253	41958	2010	3	0	35.10968	23.98387	29.5467742
12254	41958	2010	4	26	36.41667	27.14667	31.7816667
12255	41958	2010	5	136	35.15161	26.30323	30.7274194
12256	41958	2010	6	350	33.6	26.74333	30.1716667
12257	41958	2010	7	234	32.3871	26.84194	29.6145161
12258	41958	2010	8	255	32.75161	26.74839	29.75
12259	41958	2010	9	243	32.78667	26.19333	29.49
12260	41958	2010	10	324	32.39355	24.92258	28.6580645
12251	41958	2010	11	94	30.51	21.51333	26.0116667
12252	41958	2010	12	11	25.76452	15.27419	20.5193548
12261	41958	2011	1	1	24.48065	12.8	18.6403226
12262	41958	2011	2	2	29.12857	16.57143	22.85

12265	41958	2011	3	11	33.02258	21.04839	27.0354839
12266	41958	2011	4	109	34.46333	23.82333	29.1433333
12267	41958	2011	5	137	34.76129	25.89677	30.3290323
12268	41958	2011	6	494	33.10667	26.56333	29.835
12269	41958	2011	7	386	32.31935	26.5	29.4096774
12270	41958	2011	8	647	31.05484	26.04194	28.5483871
12271	41958	2011	9	429	31.52	25.93	28.725
12272	41958	2011	10	49	33.0871	24.94516	29.016129
12263	41958	2011	11	11	30.19333	19.77	24.9816667
12264	41958	2011	12	12	25.11613	15.55161	20.333871
12273	41958	2012	1	40	24.52581	14.80645	19.666129
12274	41958	2012	2	13	29.43448	16.27931	22.8568966
12277	41958	2012	3	8	33.93871	22.32903	28.133871
12278	41958	2012	4	85	34.87333	24.52333	29.6983333
12279	41958	2012	5	61	35.67097	26.93548	31.3032258
12280	41958	2012	6	193	34.83333	27.68667	31.26
12281	41958	2012	7	359	32.36129	26.70645	29.533871
12282	41958	2012	8	449	32.35161	26.48387	29.4177419
12283	41958	2012	9	420	32.00333	26.37	29.1866667
12284	41958	2012	10	114	31.95806	23.91613	27.9370968
12275	41958	2012	11	34	28.90667	19.54667	24.2266667
12276	41958	2012	12	8	24.93226	14.25806	19.5951613
high value per yr							

Source: http://www.barc.gov.bd/dbs/index.php?t=ym_rainfall

APPENDIX B

Results of ROI Separability Tests 1988329 & 2011312

```
ROI Separability Report
File
Input File: 1988329_sr_stkC.tif
    ROI Name: (Jeffries-Matusita, Transformed Divergence)

ROI_2011 [Name=Water]:
    ROI_2011 [Name=developed]: (1.48703285 1.92437421)
    ROI_2011 [Name=mangroves]: (1.99974382 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.76027019 1.99983418)
    ROI_2011 [Name=shrimp]: (1.26197492 1.64585627)

ROI_2011 [Name=developed]:
    ROI_2011 [Name=Water]: (1.48703285 1.92437421)
    ROI_2011 [Name=mangroves]: (1.99440786 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.31927810 1.53578692)
    ROI_2011 [Name=shrimp]: (0.80731587 0.89205200)

ROI_2011 [Name=mangroves]:
    ROI_2011 [Name=Water]: (1.99974382 2.00000000)
    ROI_2011 [Name=developed]: (1.99440786 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.99952018 2.00000000)
    ROI_2011 [Name=shrimp]: (1.99711409 2.00000000)

ROI_2011 [Name=rice_crops]:
    ROI_2011 [Name=Water]: (1.76027019 1.99983418)
    ROI_2011 [Name=developed]: (1.31927810 1.53578692)
    ROI_2011 [Name=mangroves]: (1.99952018 2.00000000)
    ROI_2011 [Name=shrimp]: (0.74449988 0.95104646)

ROI_2011 [Name=shrimp]:
    ROI_2011 [Name=Water]: (1.26197492 1.64585627)
    ROI_2011 [Name=developed]: (0.80731587 0.89205200)
    ROI_2011 [Name=mangroves]: (1.99711409 2.00000000)
    ROI_2011 [Name=rice_crops]: (0.74449988 0.95104646)

Pair Separation (least to most);

ROI_2011 [Name=rice_crops] and ROI_2011 [Name=shrimp] - 0.74449988
ROI_2011 [Name=developed] and ROI_2011 [Name=shrimp] - 0.80731587
ROI_2011 [Name=Water] and ROI_2011 [Name=shrimp] - 1.26197492
ROI_2011 [Name=developed] and ROI_2011 [Name=rice_crops] - 1.3192781
ROI_2011 [Name=Water] and ROI_2011 [Name=developed] - 1.48703285
ROI_2011 [Name=Water] and ROI_2011 [Name=rice_crops] - 1.76027019
ROI_2011 [Name=developed] and ROI_2011 [Name=mangroves] - 1.99440786
ROI_2011 [Name=mangroves] and ROI_2011 [Name=shrimp] - 1.99711409
ROI_2011 [Name=mangroves] and ROI_2011 [Name=rice_crops] - 1.9995201
ROI_2011 [Name=Water] and ROI_2011 [Name=mangroves] - 1.99974382
```

```
ROI Separability Report
File
Input File: 2011_312_sr_stkC.tif
    ROI Name: (Jeffries-Matusita, Transformed Divergence)

ROI_2011 [Name=Water]:
    ROI_2011 [Name=developed]: (1.90341535 1.99999492)
    ROI_2011 [Name=mangroves]: (2.00000000 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.99999623 2.00000000)
    ROI_2011 [Name=shrimp]: (1.96987119 1.99999811)

ROI_2011 [Name=developed]:
    ROI_2011 [Name=Water]: (1.90341535 1.99999492)
    ROI_2011 [Name=mangroves]: (1.98660455 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.72388393 1.99727561)
    ROI_2011 [Name=shrimp]: (0.98560903 1.43764457)

ROI_2011 [Name=mangroves]:
    ROI_2011 [Name=Water]: (2.00000000 2.00000000)
    ROI_2011 [Name=developed]: (1.98660455 2.00000000)
    ROI_2011 [Name=rice_crops]: (1.97182297 1.99684735)
    ROI_2011 [Name=shrimp]: (1.94575589 1.99999970)

ROI_2011 [Name=rice_crops]:
    ROI_2011 [Name=Water]: (1.99999623 2.00000000)
    ROI_2011 [Name=developed]: (1.72388393 1.99727561)
    ROI_2011 [Name=mangroves]: (1.97182297 1.99684735)
    ROI_2011 [Name=shrimp]: (0.98701872 1.39669817)

ROI_2011 [Name=shrimp]:
    ROI_2011 [Name=Water]: (1.96987119 1.99999811)
    ROI_2011 [Name=developed]: (0.98560903 1.43764457)
    ROI_2011 [Name=mangroves]: (1.94575589 1.99999970)
    ROI_2011 [Name=rice_crops]: (0.98701872 1.39669817)

Pair Separation (least to most);

ROI_2011 [Name=developed] and ROI_2011 [Name=shrimp] - 0.98560903
ROI_2011 [Name=rice_crops] and ROI_2011 [Name=shrimp] - 0.98701872
ROI_2011 [Name=developed] and ROI_2011 [Name=rice_crops] - 1.72388393
ROI_2011 [Name=Water] and ROI_2011 [Name=developed] - 1.90341535
ROI_2011 [Name=mangroves] and ROI_2011 [Name=shrimp] - 1.94575589
ROI_2011 [Name=Water] and ROI_2011 [Name=shrimp] - 1.96987119
ROI_2011 [Name=mangroves] and ROI_2011 [Name=rice_crops] - 1.97182297
ROI_2011 [Name=developed] and ROI_2011 [Name=mangroves] - 1.98660455
ROI_2011 [Name=Water] and ROI_2011 [Name=rice_crops] - 1.99999623
ROI_2011 [Name=Water] and ROI_2011 [Name=mangroves] - 2.00000000
```