A Review of Satellite Remote Sensing Techniques of River Delta Morphology Change

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Abstract

River deltas are important coastal depositional systems that are home to almost half a billion people worldwide. Understanding morphology changes in deltas is important in identifying vulnerabilities to natural disasters and improving sustainable planning and management. Satellite remote sensing has shown to be a useful technology for analyzing these morphology changes owing largely to its capability to provide spatially continues observations. In this paper, we critically review the literature about satellite remote sensing techniques that were used to study delta morphology changes.

We identify and categorize the techniques reported in the literature into 3 major classes: 1) One-step change detection, 2) Two-step change detection, and 3) Ensemble Classifications. In total we offer a review of 18 techniques within these categories. Example studies, the strengths and caveats in relation to the deltaic environment are discussed for each technique. Our synthesis of the literature reveals that sub-pixel-based algorithms perform better than pixel-based ones. Machine learning techniques rank second to sub-pixel techniques although an ensemble of techniques can be used just as effectively to achieve high feature detection accuracies.

We evaluate the 7 most commonly used techniques in literature (Conventional Techniques: (1) Modified Normalized Difference Water Index (MNDWI), 2) Normalized Difference Water Index (NDWI), 3) PCA analysis, 4) Unsupervised Classification, and 5) Supervised Classification)]. Machine Learning techniques: 6) Random Forest Classifier, and 7) Support Vector Machine) on a sample of global deltas, for delta morphological feature extraction performance. Findings show the Unsupervised Classification significantly outperforms the others and is recommended as a first order feature extraction technique in previously unknown, or, data sparse deltaic territories.

We propose four pathways for future advancement in satellite remote sensing of delta morphology: 1) utilizing new high-resolution imagery and development of more efficient data mining techniques, 2) moving toward universal applicability of algorithms and their transferability across satellite platforms, 3) improvement of the availability and use of ancillary data in image processing algorithms, and 4) development of a global-scale repository of deltaic data for the sharing of scientific knowledge across regions and disciplines.

1. Introduction

1.1 The River Delta and its Importance

A river delta is defined as a discrete shoreline protuberance formed from deposition of sediment where rivers enter oceans, semi enclosed seas (coastal embayments), lakes or lagoons (adapted from Elliott, 1986). Deltaic regions are home to more than 490 million people, including several megacities (Syvitski & Saito, 2007). These hubs act as major centers for agriculture (Syvitski & Saito, 2007), fisheries (Woodroffe *et al.*, 2006), and hydrocarbon production (Syvitski *et al*., 2009), offering employment opportunities for millions, and consequently making deltaic regions some of the most economically productive systems in the world (Woodroffe *et al*., 2006). The ecological significance of river deltas lies in the fact that they act as coastal storm surge protectors, biodiversity hotspots, provide habitats for many animal and plant species, provide pathways for migratory species and carry with them a cultural heritage which is a high revenue generation mechanism for local communities (Hutchings & Campbell, 2005; Lentz *et al*., 2016).

1.2 The Morphology of a Delta

Morphology, in the simplest of terms, is the configuration or form of a river delta in its natural environment. The morphology of modern deltaic systems (so named because their formation/progradation began during the late Holocene period, subsequent to the last glacial period; Allison *et al.*, 2003) is controlled by the complex interaction between boundary conditions and forcing factors (Coleman and Wright, 1975; Orton and Reading, 1993; Postma, 1995; Syvitski and Saito, 2007). These forcing factors include (1) supply of bedload and suspended sediment load: reflecting drainage basin characteristics, water discharge, sediment yield and grain size; (2) deposition/accommodation space: reflecting sea-level fluctuations, offshore bathymetry, tectonics, subsidence, compaction, and isostasy; (3) coastal energy: reflecting waves and tides, longshore and cross-shelf transport; and (4) density differences between effluent and receiving waters defining the dynamics of sediment plumes. The complex interaction between these factors result in the formation of different features (e.g. main delta landmass governed by the delta shoreline, sandbars/barrier islands, beach spits). These features, which are component environments of the delta, collectively describe the morphology of the delta, reflect the status quo of the river delta, and can be used to monitor changes to the delta through time.

1.3 Importance of Delta Morphology Change Studies

Most modern deltas serve societal needs such as protecting residents, resources, and infrastructure, or preserving biodiversity and ecosystem services. Human settlements and infrastructure in low-lying deltaic regions are particularly vulnerable to floods induced by intense precipitation and storm surges (Motsholapheko *et al.*, 2011; Sanchez-Arcilla *et al.*, 2012). Floods disrupt cultivation in delta plains, livestock farming, destroy property leading to displacement of households, interrupt water reticulation systems, and curtail transport systems, thereby impacting a country's economic growth significantly (Bendsen and Meyer, 2002; Motsholapheko *et al.*, 2011). Therefore, knowledge on morphology change is important to plan engineering works such as identification of vulnerable areas, installation of coastal defense structures (e.g. breakwaters, weirs), confinement or widening of river channels, dredging, sand extraction, dam construction, development of setback planning and hazard zoning.

In addition to mitigate against flooding, delta morphology change information is also important for constructing engineering structures for transport, land reclamation and urbanization, erosion-accretion studies, regional sediment budgets, restoration activities for extensively altered deltas, and for conceptual or predictive modeling of coastal morphodynamics (Sherman and Bauer, 1993, Al Bakri, 1996, Zuzek *et al*., 2003; see Maiti and Bhattacharya (2009); Masria *et al*., 2015; Le *et al*., 2007). Therefore, understanding and predicting these morphology change dynamics is of utmost importance for sustainable planning of deltaic communities.

1.4 Satellite Remote Sensing of Deltaic Morphology Dynamics

During the past four decades satellite remote sensing technologies have emerged as a viable alternative to in-situ observations of river deltas and associated deltaplain morphology changes (Figure 1: evolution of the Yellow river delta during the satellite era). This is mainly attributed to their availability over large geographical regions, the effectiveness of the delta-change mapping techniques, the temporal coverage of a given location, and the relatively low cost for large aerial extents (Mathers and Zalasiewicz, 1999; Zhao *et al.,* 2008; Zhang *et al.,* 2015; Munasinghe *et al.,* 2018). Although delta morphology mapping based on ground surveys and aerial observations (e.g. aerial photography, drone footage) is a viable and useful option, such methods are time-consuming, expensive and, in most cases, cannot provide data on time scales commensurate with delta morphology change. Remotely sensed data can be seamlessly used as a stand-alone tool, or in tandem with complementary numerical modeling and statistical efforts.

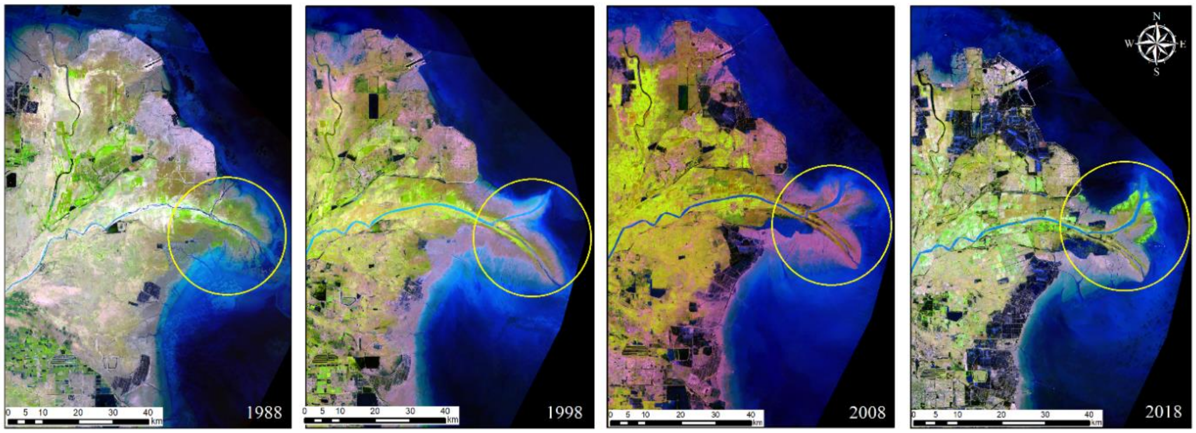


Figure 1: Landsat satellite imagery showing the evolution of the Yellow River Delta, China from 1988 to 2018. The circled area shows the downward development of the Qingshuigou Lobe, and the more prominent upward development of the Qing8 Lobe of the delta.

1.5 Motivation for this Review

The impetus for this review comes from the non-availability of a single robust document in the literature which portrays past and current research efforts in identifying river delta morphology changes using satellite remote sensing techniques. The need for such a summation stems from several reasons. Morphology detection techniques that work well for one particular river delta might not be ideal for another: This could be due to complications of geometries of river deltas (e.g. influenced by islands, sandbars), sediment plumes transported by rivers (gradational deposition at the river mouth) making the identification of the delta boundaries difficult, geographical location of river delta (governs the type and density of vegetation that grows at the land-sea margin), and tidal forces (determines formation of islands close to the main delta body due to breakage) which all act in varying degrees in determining the performance accuracy of algorithms. This has led to morphology detection algorithms to mostly be location specific. A summation of knowledge as such also aids in morphology detection algorithm selection and application to lesser studied deltaic systems globally, done informatively. The transfer of knowledge from prior use cases could be done optimistically (by relative comparison of similar delta forms and geographical regions) and with caution (prior understanding of limitations of detection algorithms). Thus, for current research frontiers in deltaic research to expand, a need arises for a comprehensive, organized summary of historical and emerging techniques of delta change mapping of key deltaic environments.

We also perform a comparison of remote sensing techniques on an array of delta types (river-, tide-, wave-dominated) from a global sample of deltas to understand the performance of techniques under varying fluvial and marine conditions. Elucidating which technique(s) work best in delta morphological feature extraction would allow us to infer why particular techniques underperform in different regions of the world. This will also highlight some of the inherent problems of particular techniques and will offer a pathway for improving existing algorithms and development of new ones to monitor river delta morphological change.

This document reviews the content of 146 articles/book chapters which used remote sensing technologies to detect deltaic features and their changes, and a further 38 articles/book chapters to gather supplementary information on river delta research and technological advances in computational algorithm development. Every effort has been taken to cover the breadth of remote sensing techniques that were used in delta morphology research from 1980 until present day.

2. Indicators of Delta Morphology Change

A river delta is a collection of different component environments (as described in section 1.2). Changes to these components result in the changes in geometries, sediment facies and depositional architecture of the delta. Thus, these components can be used as ‘indicators’ to assess changes to the morphology and can be quantitatively used to derive delta evolution. For example, a decrease in sediment fluxes to the delta can move it from a condition of active growth to a destructive phase portrayed by the recession of the land-sea margin (i.e. the delta shoreline). In a second example, strong wave climates effectively diffuse fluvial sediment, thereby limiting mouth bar growth and make the delta mainland more erosion prone, and vice versa. Therefore, as per the above two examples, the delta shoreline and presence/absence of mouth bars can be used as indicators to assess changes to river delta morphology.

Although there exist a plethora of morphology change indicators, it has to be noted that the focus of this review will only be on, a) indicators that can be identified using satellite remote sensing (e.g. shelf depth, (water depth reached by the submerged delta), although a factor governing delta morphology, cannot be assessed using satellite remote sensing), and b) indicators that directly reflect morphology-change of a delta (e.g. indicators reflecting changes to the effective deltaic landmass (i.e. the shoreline)) as opposed to indicators of forcing factors which act as causal factors of morphology change (e.g. drainage basin-averaged climate, which in turn can have an effect on erosion of delta plain and sediment loading into feeder river).

Based on above selection criteria, we categorize all satellite-detectable indicators which reflect morphology change into 5 classes summarized from studies conducted by Syvitski and Saito (2007), Mathers and Zalasiewicz, (1999), Ulrich *et al.* (2009), Passalacqua, (2017). Table 1 provides an overview of these indicators, and the role they play in structuring the overall morphology of the delta.

Table 1: Change indicators and their representation of delta morphology

Class	**Indicator**	**Role of Indicator in Delta Morphology Change Representation**	**Can be Remotely Sensed? (Y/N)**	**Included in Review? (Y/N)**
1	Shoreline	Governs the land-sea margin, determines the effective landmass available for human consumption, and determines subaerial view (plan view) of the delta.	Y	Y
2	Crevasse Splays and Channel Avulsions	Channel avulsions in deltaic areas start with the formation of a crevasse splay. Crevasse splays (deposits of sediment in the shape of a fan or lobe formed by river channels as a result of point failures of a levee) help better understand how rivers naturally distribute water and sediment across floodplains, local rates of sediment accumulation and sediment delivery to coastal regions, and influences on floodplain topography and alluvial architecture, and help make informed decisions on land-management solutions such as engineered diversions (Nienhuis et al., 2018).	Y	Y
3	Number and Size of Distributary Channels, and Meander belts	Avulsions and other channels on the delta make up the distributary network. Proper understanding of the size of the distributary channels and the ways in which they migrate through time is critical to many geomorphological and river management problems on a delta (Seker et al., 2005; Yang et al., 1999). Channel erosion and bank failure cause obstruction of navigation routes, changes to channel geomorphology, and most importantly changes to flood levels which can have adverse impacts on the infrastructure of the delta plain.	Y	Y
4	Barrier Islands, Beach Spits, and Mouth Bars	These are deltaic features that result from the dynamic interaction of fluvial sediment supply and the redistribution of sediment by marine processes at the river mouth-sea interface. Rapid deposition on river-mouth bars can cause their seaward progradation, which, through the control of upstream siltation in the main river channel, can serve as a stimulus to river channel migration. Heavy	Y	Y

		sedimentation in the lower reaches of the river channel can also cause the riverbed to aggrade and increases the flood risk on the floodplain, making the river channel avulsion-prone. Beach spits and barrier islands function more in the capacity of coastal storm surge attenuation and wave and tidal erosion control which impact the shoreface.		
5	Gradient of Delta Plain	Measured from the apex of the delta to the coast along the main channel (Syvitski and Saito, 2007), the gradient of the delta plain is a vertical measure of morphology. This in addition to the sediment supply to sediment retention on the delta plain, can be significantly impacted by subsidence of the delta plain itself. Subsidence related morphological changes to the gradient might not be reflected by the land-sea boundary but can be reflective in flood extents during extreme events which impact floodplain architecture.	Y	*N

* studies pertaining to the gradient of the delta plain will not be discussed in this review for two reasons. Firstly, the majority of the studies related to the gradient in the literature are from a geological perspective without any substantial remote sensing component to them. Thus, they do not scope well within the constraints of this review. Secondly, even the studies that did discuss remotely sensed changes in river delta gradient, were done so as secondary derivatives of changes in land subsidence of the delta. Subsidence mapping is an entirely vast and different field of remote sensing which would constitute a separate review of its own.

The change in deltaic shoreline can be regarded as the most important environmental descriptor of delta morphology, as it is the only parameter that reflects the 'quantity' of landmass available for human consumption indicating how the delta front prograded or degraded over the years. In comparison, other indicators detect morphology changes 'on' the deltaic landmass and thus has garnered a lesser importance in literature (over 90% of the studies reviewed for morphology change were based on the shoreline). Delta shoreline changes are described in section 3, and studies discussing all other indicators are summarized in section 4.

3. Delta Shoreline Change Detection Techniques

Delta progradation/degradation determination through remote sensing relies on the varied spectral response of the land-water boundary (i.e. the shoreline) at different wavelengths. Different landforms produce characteristic surface spectral responses as products of the combination of the terrain color and surface moisture linked with composite materials, texture and structure properties of the exposed portions, terrain geometry and land cover. A large number of techniques for delta progradation detection from satellite imagery have been developed over the years and can be classified into three broad categories of change detection methods (Figure 2): 1) Two-step Change Detection: use of a remote sensing technique(s) to delineate morphology for a particular time step, use the same or different set of technique(s) to retrieve morphology at a different time step and compare between them; 15 such techniques will be discussed, 2) One-step change detection: The use of a remote sensing technique(s) on multidate imagery to detect change in one step; two such techniques will be discussed: a) Layer Arithmetic: use of band mathematics on the reflectance values to compare between multi-date imagery, b) Change Vector Analysis: use of the radiometric properties of multi-date imagery to yield both magnitude and direction of change, and 3) Ensemble Classification: use of a mixed methods approach.

It is important to note, and user applications need to pay attention to the fact that, the location of a shoreline on a satellite image might not be the topographical boundary between land and water as it is an instantaneous one influenced by seawater level fluctuations caused by waves, tides and local seasonal sea level changes. Therefore, it would be erroneous to apply said shoreline detection techniques to a single image representative of a time step, as these external forces can substantially affect water levels (Walker and Hammack, 2000) and consequently the boundary, without necessarily indicating a morphological change. There are statistical methods to correct for the shoreline position (Zhang *et al.*, 2018) if changes of shorter time steps are desired (e.g. change every year during a 5-year period). For longer time scale analysis (e.g. change every 5 years for a 30-year period), a composite, representative of the deltaic region, using imagery over a few consecutive months (e.g. 6 months), is created, and the averaged raster is used as a single time step.

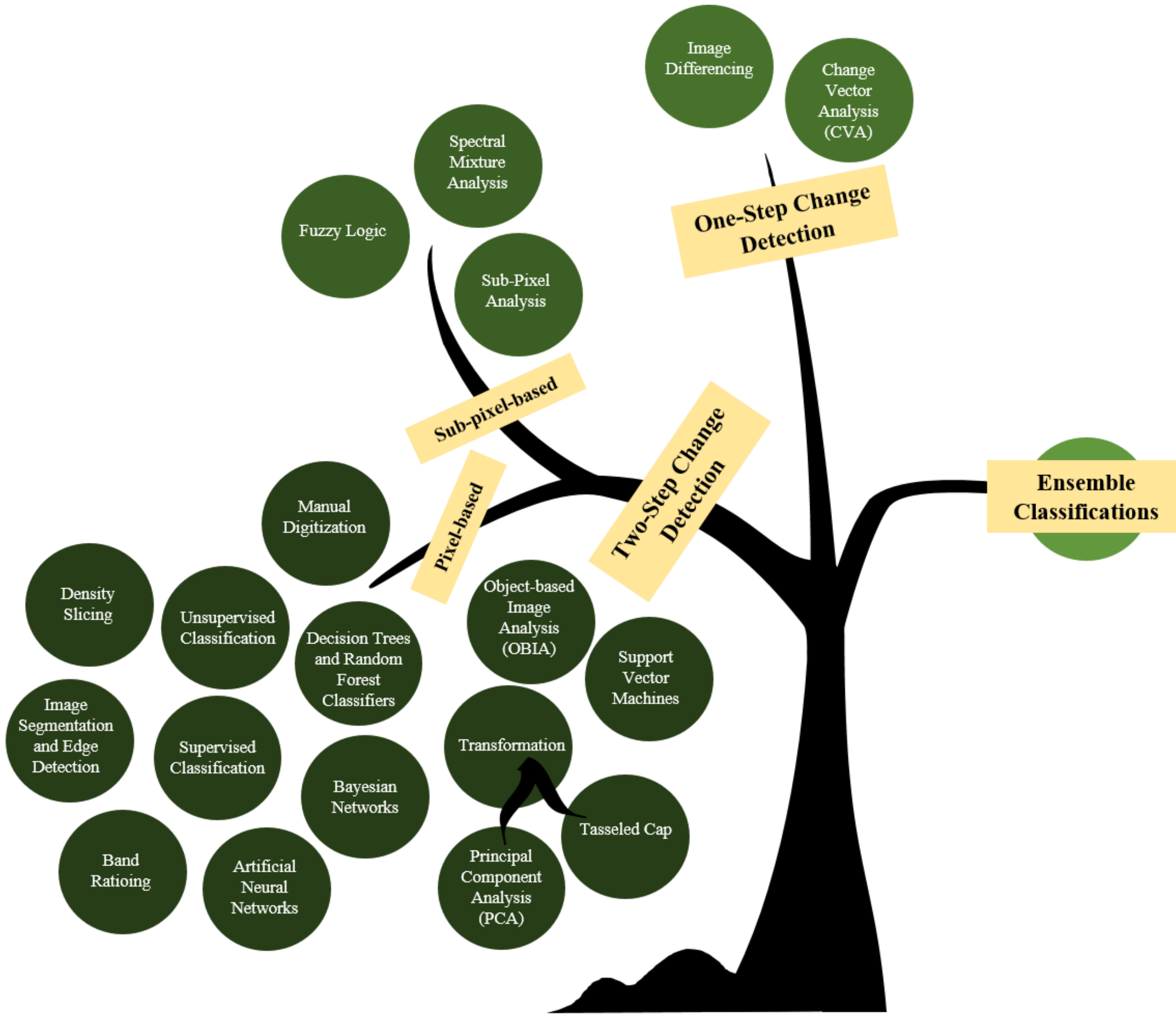


Figure 2: Classification of remote sensing techniques used for river delta morphology change detection

The discussion of each technique is framed on the conceptual background of the technique, how and why it is applied to deltaic feature detection, the technical merit of application, and its caveats informed by the conclusions and recommendations of the literature reviewed. We present a summary of all techniques reviewed in this paper along with example studies in Table 2 below for the readership to revert to, during the length of the document, as a quick reference guide.

Table 2: A summary of remote sensing techniques of river delta morphology change identification

Technique	Example Studies	River Delta (Country)	Satellite Platform
Manual Digitization	Yang (1996)	Yellow (China)	Landsat MSS, Landsat TM
	Yang *et al.* (1999)	Yellow (China)	Landsat MSS, Landsat TM
	Chu *et al.* (2006)	Yellow (China)	Landsat MSS, Landsat TM
	Zhao *et al.* (2008)	Yangtze (China)	Landsat TM, Landsat ETM+
	Marghany *et al.* (2010)	Kuala Terengganu (Malaysia)	ERS-1, RADARSAT-1
	El Asmar and Hereher (2011)	Nile (Egypt)	Landsat MSS, Landsat TM, SPOT-4
	Kuenzer *et al.* (2014)	Yellow (China)	Landsat MSS, Landsat TM
	Duțu *et al.* (2014)	Danube (Romania/Ukraine)	Landsat TM, Landsat ETM+
	Ahmed *et al.* (2018)	Ganges-Brahmaputra-Meghna (India)	Landsat TM, Landsat ETM+
Density Slicing	Mouchot *et al.* (1991)	Mackenzie (Canada)	Landsat TM
	Mathers and Zalasiewicz (1999)	Red (Vietnam)	Landsat TM
	Ryu *et al.* (2002)	Gosmo Bay (Korea)	Landsat TM, ASTER
	Maiti and Bhattacharya (2009)	Subarnarekha and Rasulpur (India)	Landsat MSS, Landsat TM, Landsat ETM+, ASTER
	Mallinis *et al.* (2011)	Nestos (Greece)	Quickbird
	Allen *et al.* (2012)	Wax Lake (USA)	Landsat TM, Landsat ETM+
	Kong *et al.* (2015)	Yellow (China)	Landsat MSS, Landsat TM, Landsat ETM+
	Ghoneim *et al.* (2015)	Nile (Egypt)	Landsat MSS, Landsat TM, Landsat ETM+
	Dada *et al.* (2018)	Niger (Nigeria)	Landsat TM, Landsat ETM+
Image Segmentation and Edge Detection	Lee and Jurkevich (1990)	Chesapeake Bay (USA)	Saesat, Shuttle Imaging Radar (SIR)
	Mason and Davenport (1996)	Wash delta/estuary (UK)	ERS-1
	Niedermeier *et al.* (2000)	Elbe (Germany)	ERS-1 and ERS-2
	Bayram *et al.* (2008)	Bhosporous (Turkey)	Corona, IRS-1D, Landsat ETM+
	Al Fugura *et al.* (2011)	Kuala Terrenganu (Malaysia)	RADARSAT-1
Band Ratioing	Yang *et al.* (1999)	Yellow (China)	Landsat MSS, Landsat TM
	El-Raey *et al.* (1999)	Nile (Egypt)	Landsat MSS
	Ryu *et al.* (2002)	Gosmo Bay (Korea)	Landsat TM, ASTER

	Guariglia *et al.* (2006)	Ionian coast (Italy) inclusive of deltas	Landsat TM, Landsat ETM+, SPOT XS, Corona
	Ekercin (2007)	nothern coast of Turkey including deltas	Landsat MSS, Landsat TM, Landsat ETM+
	Kuleli (2010)	Cukurova (Turkey)	Landsat TM
	Cui and Li (2011)	Yellow (China)	Landsat MSS, Landsat TM, Landsat ETM+
	Mukhopadhyay *et al.* (2012)	Puri coast and Mahanadi (India)	Landsat TM
	Niya *et al.* (2013)	Dalaki (Iran)	Landsat TM
	Kundu *et al.* (2014)	Sagar Island, GBM (India)	Landsat TM
	Louati *et al.* (2015)	Medjerda (Tunisia)	Landsat TM, Landsat ETM+, Landsat OLI
	Nitze and Grosse (2016)	Lena (Russia)	Landsat TM, Landsat ETM+, Landsat OLI
	Sun *et al.* (2018)	Yangtze (China)	Landsat MSS, TM, OLI, GF-1 PMS, SPOT-7
	Wang *et al.* (2019)	Yellow (China)	Landsat TM, Landsat OLI
	Da Silva *et al.* (2019)	Parnaíba (Brazil)	Landsat MSS, TM, ETM+, OLI
	Viaña-Borja and Ortega-Sánchez (2019)	Guadalfeo, Adra, and Ebro (Spain)	Landsat TM, Landsat ETM+, Landsat OLI
Unsupervised Classification	Wilson (1997)	Fitzroy (Australia)	Corona
	Frihy *et al.* (1998)	Nile (Egypt)	Landsat MSS, Landsat TM
	Guariglia *et al.* (2006)	Ionian coast (Italy) inclusive of deltas	Landsat-TM, Landsat ETM+, SPOT-PX/XS, Corona
	Ekercin (2007)	nothern coast of Turkey including deltas	Landsat MSS, Landsat TM, Landsat ETM+
	Nath and Deb (2010)	Okavango Delta (Botswana)	AVHRR
	Mukhopadhyay *et al.* (2012)	Puri coast and Mahanadi (India)	Landsat TM
	Muster *et al.* (2012)	Lena (Russia)	Proba -1
	Kundu *et al.* (2014)	Sagar Island of the GBM (India)	Landsat TM
	Buono *et al.* (2017)	Yellow (China)	RADARSAT-2
Supervised Classification	Sgavetti and Ferrari (1988)	Po and Adige (Italy)	Landsat TM
	Ciavola *et al.* (1999)	Shkumbini, Semani and Vjosë (Albania)	Landsat TM
	Seker *et al.* (2003)	Riva (Turkey)	Landsat MSS, Landsat TM, Landsat ETM+
	El-Kawya *et al.* (2011)	Nile (Egypt)	Landsat TM, Landsat ETM+
	Masria *et al.* (2015)	Nile (Egypt)	Landsat TM, Landsat ETM+

Transformation Methods			
Principal Component Analysis (PCA)	El Raey *et al*. (1995)	Nile (Egypt)	Landsat MSS, Landsat TM
	Li and Yeh (1998)	Pearl (China)	Landsat TM
	Kushwaha *et al.* (2000)	West Bengal coast inclusive of deltas (India)	ERS-1
	Seto *et al*. (2002)	Pearl (China)	Landsat TM
	Li and Yeh (2004)	Pearl (China)	Landsat TM
	Ghanavati *et al*. (2008)	Hendijan (Iran)	Landsat TM, Landsat ETM+
	Ghoneim *et al*. (2015)	Nile (Egypt)	Quickbird, Worldview-2
Tasseled Cap Transformation	Nandi *et al.* (2016)	Sagar Island, GBM (India)	Landsat MSS, Landsat TM, Landsat ETM+
	Chen *et al.* (2019)	Yangtze (China)	Landsat OLI
Artificial Neural Networks (ANN)	Berberoglu *et al.* (2000)	Cukurova (Turkey)	Landsat TM
	Zhu (2001)	Pearl (China)	Landsat MSS, Landsat TM
	Del Frate *et al.* (2012)	Italian coastline inclusive of deltas	COSMO-SkyMed
	Ding (2013)	Yellow (China)	Landsat TM, Landsat ETM+
Decision Trees and Random Forest Classifiers	Ottinger *et al.* (2013)	Yellow (China)	Landsat TM
	Kuenzer *et al.* (2014)	Niger (Nigeria)	Landsat TM, Landsat ETM+
	Haas and Bun (2014)	Yellow, Pearl (China)	Landsat TM, HJ-1A/B satellites
	Banks *et al.* (2015)	Kitikmeot region (Canada) inclusive of deltas	RADARSAT-2, Landsat TM
	Berhane *et al.* (2018)	Selenga (Russia)	Worldview-2
Bayesian Networks	Gutierrez *et al.* (2011)	U.S. Atlantic Coast inclusive of deltas	
	Yates and Cozannet (2012)	European coasts inclusive of deltas	Areal observations used as input
Support Vector Machines	Xu *et al.* (2012)	Yellow (China)	RADARSAT-2
	Masria *et al.* (2015)	Nile (Egypt)	Landsat TM, Landsat ETM+
	Petropoulos *et al.* (2015)	Axios and Aliakmonas (Greece)	Landsat TM
	Gou *et al.* (2016)	Yellow (China)	ALOS-2

Object-based Image Analysis	Cao *et al.* (2007)	Yellow (China)	SPOT 5
	Liu *et al.* (2014)	Yellow (China)	Landsat TM, Landsat ETM+, HJ-1A/B satellites
	Demers *et al.* (2015)	Islands of Mackenzie Delta (Canada)	RADARSAT-2
	Zhu *et al.* (2018)	Yellow (China)	Landsat MSS, Landsat TM, Landsat OLI
Fuzzy Logic	Dellepiane *et al.* (2004)	coastline in Genova (Italy) inclusive of deltas	ERS-1, ERS-2
	Foody *et al.* (2005)	coast in Terengganu (Malaysia) inclusive of deltas	IKONOS
	Ghanavati *et al.* (2008)	Hendijan (Iran)	Landsat TM, Landsat ETM+
	Dewi *et al.* (2016)	deltaic region in the Sayung District (Indonesia)	Landsat TM, Landsat ETM+, Landsat OLI
Spectral Mixture Analysis	Liu *et al.* (2016)	Yellow (China)	Landsat OLI
	Liu *et al.* (2017)	Pearl (China)	Landsat OLI
Sub-Pixel Analysis	Wei *et al.* (2008)	Yellow (China)	ASTER
Image Differencing	Yeh and Li (1997)	Pearl (China)	Landsat MSS, Landsat TM
	Xia (1998)	Pearl (China)	Landsat TM
	El-Raey *et al.* (1999)	Nile (Egypt)	Landsat MSS
	Adegoke (2010)	Niger (Nigeria)	Landsat TM, Landsat ETM+
Change Vector Analysis	El-Raey *et al.* (1999)	Nile (Egypt)	Landsat MSS
	Seto *et al.* (2002)	Pearl (China)	Landsat TM

3.1 Classification Techniques used in Two-Step Change Detection

3.1 (A) Pixel-Based Methods

3.1.1 Manual Digitization

Deltaic coastlines are delineated manually based on the delineator's/digitizer's knowledge of the morphological features, vegetation and sediment characteristics of the delta. Compared to computer aided classification techniques, manual operation takes advantage of the judgment skills and interpretation of humans in defining what and where the boundary is between land and water.

The combination of digitization and automatic boundary detection algorithms (discussed later) to detect the land–ocean shoreline boundaries were proven to be successful (Kong *et al*., 2015). However, this technique has several inherent problems. In addition to the inaccuracies induced through the monotonous nature of digitization, it is also challenging for the human eye to interpret the boundary (based largely on digitizer's experience) since, mainly in low-resolution images, color shades may decay gradually (Niedermeier *et al*., 2005). Presence of water saturated zones in the vicinity of the land water boundary could complicate the issue. Therefore, calculations have to be performed in order to recognize if the inaccuracies constitute a significant source of error in comparison to the magnitude of the overall changes in the delta (Chu *et al*., 2006). This approach is also highly time-consuming and tedious. It is therefore expensive (labor cost) and ineffective when a large number of images need to be analyzed.

3.1.2 Density Slicing

The concept of density slicing involves classifying the remotely-sensed image into land and sea, often by identifying a threshold value for a single spectral band. In order to determine this critical threshold without bias, a histogram analysis is often performed (Figure 3). Ryu *et al.* (2002) and Shen *et al*. (2008) showed that in tidal flat zones, thermal-infrared (TIR) band is the most sensitive to the location of waterline through density slicing. Work on Landsat has shown that mid-infrared bands (band 5 in the case of Landsat TM) is the most suitable for extracting the land water interface because it exhibits a strong contrast between land and water features due to the high degree of absorption of the mid-infrared wavelength by water (Manavalan *et al*., 1993; Kelly *et al*., 1998; Frazier and Page, 2000; Lee *et al*., 2001; Alesheikh *et al*., 2007).

While overall successful, this method carries with it certain caveats. Although land and water generally appear to be spectrally separable, the accuracy of waterline prediction is sometimes low due to the dynamic and complex land-water interactions in coastal deltaic regions. This could be due to spectral confusion, arising from effects such as variable depth and turbidity, together with the spatial resolution of the imagery, which influences the clarity of boundaries and proportion of mixed pixels, limiting the accuracy of shoreline mapping (Frazier and Page, 2000; Ryu *et al*., 2002; Malthus and Mumby, 2003). Also, the use of one spectral band usually does not allow every type of change to be detected (Gong, 1993). Density slicing alone is not sufficient in determining the shoreline and, therefore, typically used in conjunction with other methods to obtain higher delta shoreline classification accuracies (Marghany *et al*., 2010).

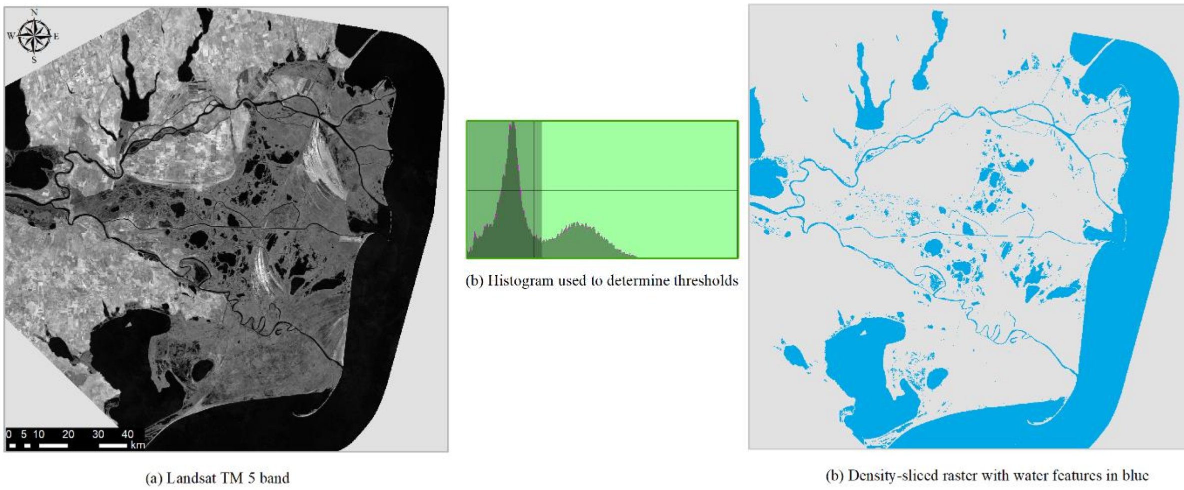


Figure 3: Density Slicing of band 5 (Landsat TM) of the Danube delta region to obtain a land-water raster. The shoreline was subsequently extracted using GIS methods.

3.1.3 Image Segmentation and Edge Detection

Image segmentation and edge detection algorithms follow the process of manual digitization more closely by dividing an image into different regions where sharp intensity alterations occur. The "alternative connective approach", one of two major image segmentation and edge detection algorithms is used in deltaic research where it seeks to grow homogeneous regions by merging pixels or sub-regions on the basis of some similarity criterion (Lemoigne and Tilton, 1995). This approach is based on 'guiding' the remote sensing software by manually identifying points along the shoreline of the original image. The software then examines the edges of the image following these points. The parameters by which the shoreline is identified are determined by the analyst. This heuristic search is found to be faster and more reliable than entirely automated approaches (Loos and Niemann, 2002) due to the input of previously gathered information by the analyst.

Albeit its success, this method also has its limitations in possible inclusion of different earth feature classes into the same region, making spectral separation and subsequent identification of thematic information classes difficult. As White and El Asmar (1999) and Heimann *et al.* (2004) stated, since the classical region growing methods (classifying neighboring pixels outward from a point of origin based on similarity of reflectance of the originating pixel) yield outcomes in accordance with the contrast of the image, contrast similarities between land and water zones impedes the extraction of coastline from other existing constituents and could result in irregularities of coastline extractions.

3.1.4 Band Ratioing

This method exploits the near infrared (NIR) and short-wave infrared (SWIR) bands whose wavelengths are absorbed by water, resulting in surface water rendered as black color in the processed image. A combination of these spectral bands ((NIR-SWIR)/(NIR+SWIR)) is used to reduce the effect of suspended sediment near shorelines (Lohani & Mason, 1999; Lodhi *et al*., 1997) and accentuate higher reflectance characteristics from soil and healthy vegetation, providing a context for the land/water interface (Braud and Feng, 1998; Fraizer and Page, 2000; Guariglia *et al*., 2006). In comparison to other methods, ratioing is a relatively rapid means of identifying areas of change.

However, there are certain downsides to this method. The Band 2/Band 5 ration has a value greater than one for water and less than one for land in large areas of the coastal zone (Alesheikh *et al*., 2007). Image processing software use this ratio as an algorithm for separating water from land from TM or ETM+ imagery. This ratio works well in coastal zones covered by soil, but not in land with vegetative cover. This can lead to mistakenly classifying other land use types as water (Alesheikh *et al*., 2007). Therefore, this is a readily go-to method if the aim is to rapidly extract the coastline. However, if the goal is accurate coastline extraction, then this might not be the most suitable. Figure 4 below shows an example application we conducted on the Irrawaddy delta in the shoreline extraction process using Landsat-8 imagery.

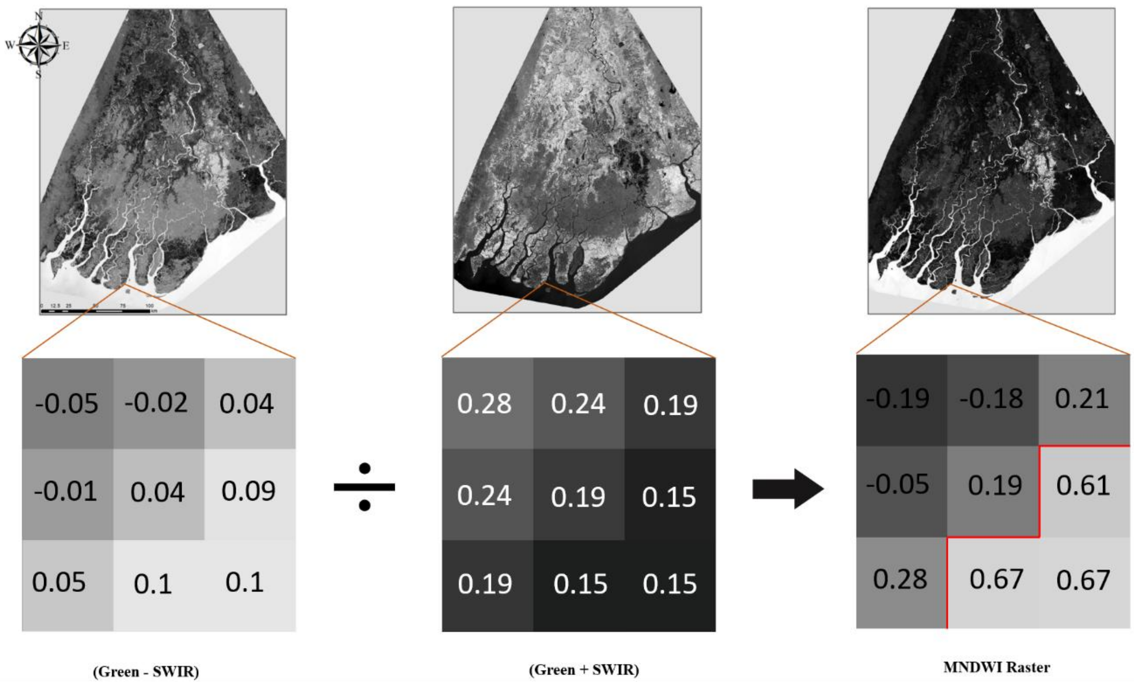


Figure 4: Band ratioing of Landsat-OLI imagery of the Irrawaddy river delta to produce a land-water raster after which the shoreline is extracted using GIS methods. The combination and ratio used here is the Modified Normalized Water Index (MNDWI; Xu, 2006) used to accentuate water features. *left:* A subtracted difference raster of Band 6 (SWIR) is and Band 3 (Green) is generated (the blow-up denotes raster values of the selected region). *Middle:* An added difference raster of Band 6 (SWIR) is and Band 3 (Green) is generated. *Right:* The difference-rasters are ratioed to produce the MNDWI feature-accentuated raster.

3.1.5 Unsupervised Classification

Unsupervised classification is an effective method of natural clustering and extracting land-cover information of remotely sensed image data based on spectral properties of pixels. Compared to supervised classification (discussed in 3.1.6), unsupervised classification requires minimal initial input from the analyst (determining the clustering algorithm and desired number of classes) as it does not require training data. The clustering process results in a classification map consisting of *n* spectral classes. The analyst then attempts to assign or transform the spectral classes into thematic information classes of interest (e.g., forest, agriculture). Many clustering algorithms have been developed to date (e.g. ISODATA Clustering, K-Means).

Unsupervised methods, although not completely exempt from the user's interaction, require less inputs than their supervised counterparts and is computationally efficient. However, the user must have knowledge of the area and understand the spectral characteristics of the terrain in order to relate the classes to actual land cover types (such as water features, wetlands, developed areas, coniferous forests, etc.). Difficulties in obtaining consistent classes from images taken at different times, owing to variability in illumination, atmospheric effects, and instrumental response, have been reported (Adams *et al*., 1995). Also, some spectral clusters may be meaningless because they represent mixed classes of earth surface materials. It has been noted in the literature that although the use of unsupervised classification is nearly a labor-independent analysis, this technique does not lead to the most detailed analysis and cannot produce the highest classification accuracy (Congalton, 1991; Xia, 1998; Enderle and Weih, 2005).

3.1.6 Supervised Classification

In Supervised classification, the analyst selects sample pixels in an image that are representative of land cover classes, and then directs the image processing software to use these end-member pixels (training pixels) as references for the classification of all other pixels in the image (determination of maximum likelihood of image pixels of a land use class based on training data). Training sites are selected based on the analyst's knowledge and experience of image interpretation. The analyst also designates the number of classes that the image is classified into.

Since supervised classification is based on prior knowledge about the land cover and their typical spectral characteristics by the analyst, this method is deemed one of the more successful methods of delta morphology detection and is commonly used as a benchmark to test other algorithms (Khatami *et al.,* 2016). Higher classification accuracies resulting from supervised classification motivated researchers to combine this technique with other methods. Shalaby and Tateishi (2007), for example, concluded that the use a combination of supervised classification and visual interpretation analysis increased the overall classification accuracy by approximately 10%. However, as the training sites are selected based on the knowledge and experience of the analyst, there is always the possibility that the sample pixels that one selects for a given information class (e.g. shoreline) will not be homogenous across the entire study domain (i.e. training areas will not encompass unique spectral signatures of a particular land feature). In addition, since this is a user driven method, it can be a time consuming and an exhaustive one, if done for multiple time steps over different study domains.

3.1.7 Transformation methods

When multispectral images are used to detect change of delta morphology, a reduction of the number of bands is often warranted in order to identify dominant patterns in the imagery (i.e. enhance the original classification feature space) without compromising the variance. Although simple band mathematics can be used and is straightforward (e.g. density slicing, band ratioing), it can be inefficient when the number of spectral bands of the image exceeds three. To overcome these difficulties the process of image transformation was introduced. Different transformation methods have been developed over the years, and two of those have been reported in delta morphological studies: Principal Component Analysis (PCA) and Tasseled Cap Analysis (TCA).

The central concept of a PCA is to reduce the dimensionality of a dataset consisting of many interrelated variables, while retaining as much variation present in the dataset as possible. This is achieved by transforming the data to a new set of variables (principal components) which are uncorrelated and ordered so that the first few retain most of the variation present in all the original variables (Deng *et al.*, 2008). The procedure works as such that subsequent to performing a PCA on multi temporal imagery, conventional clustering methods (e.g. unsupervised) can be applied to the first few principal components to produce thematic maps representative of different earth features. This method was shown to improve accuracy gains when utilized with other techniques in the image classification process (Khatami *et al.*, 2016).

Although comparatively PCA analysis has advantages over simple band mathematics techniques (i.e. band ratioing, band differencing), it introduces difficulties in interpreting and labeling each component image (to associate physical scene characteristics with the individual components). This type of analysis is also scene dependent and is difficult to obtain the 'from-to change' class information (change in pixel information from an earlier time step to a later one) when detecting change over multiple time steps. Moreover, it was found that the application of PCA for multiple time step analysis is subject to the condition that the areas of change must be a small proportion of the entire study area (Gong, 1993; Seto *et al.*, 2002).

TCA transformation rotates multispectral data and creates three planes: Brightness (B), Greenness (G) and Wetness (W) (Crist, 1985). The Brightness band is a weighted sum of all reflective bands and can be interpreted as the overall brightness or albedo at the earth's surface. The Greenness band primarily measures the contrast between the visible bands and near-infrared bands and is similar to a vegetation index. The wetness band measures the difference between the weighted sum of the visible and near-infrared bands and the mid-infrared bands and is a proxy of plant and/or soil moisture (Seto *et al.*, 2002). In TCA, the brightness, greenness, wetness bands are directly associated with physical scene attributes and therefore easily interpreted (Figure 5). TCA analyses to detect delta morphological change is seldom carried out alone and is used as a data reduction technique prior to the data being analyzed by another technique(s). Examples of the usage of TCA is given in section 4.3.

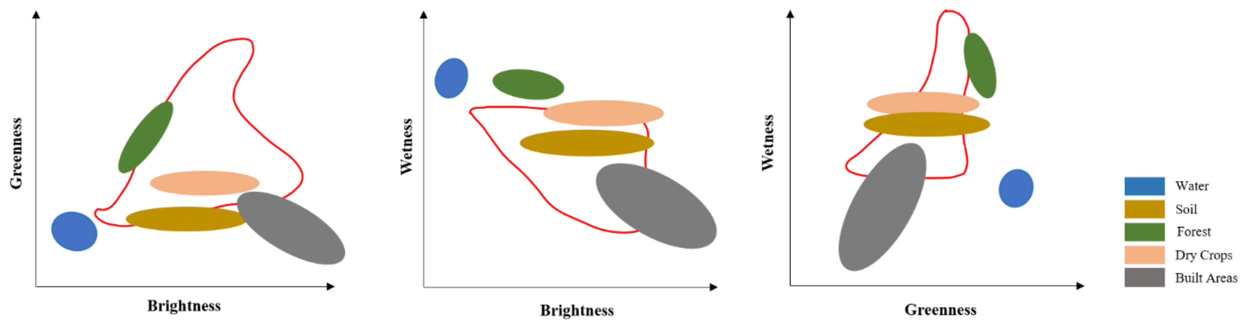


Figure 5: A typical representation of earth features between correlations of the three transformed bands.

3.1.8 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN), a form of Artificial Intelligence (AI), can be used to semi-automate image classification, and has become a common alternative to conventional band statistical approaches. The development of ANNs was inspired from human brain recognition and brain learning mechanisms (Berberoglu *et al.*, 2000). Neural networks consist of input and output layers, as well as (in most cases) a hidden layer consisting of units that transform the input into something that the output layer can use (Foody *et al.*, 1995). They are excellent tools for finding patterns which are far too complex or numerous for a human programmer to extract and train the machine to recognize (Samarasinghe, 2016).

The backpropagation algorithm (Paola and Schowengerdt, 1995) is the most common method of training multi-layer networks to date (Samarasinghe, 2016), with an emphasis on its application to pattern recognition in multispectral imagery. It allows networks to adjust their hidden layers of neurons in situations where the outcome does not match what the user is hoping for (Samarasinghe, 2016), similar to a network designed to recognize muddy shores, and misidentifies them as turbid waters.

As delta evolution is a very intricate non-linear process influenced by many factors such as the coming water and sediment discharges and coastal dynamics, neural networks possess great robustness over traditional classifiers as neural networks are also inherently nonparametric nature. The strengths of a neural network lie in arbitrary decision boundary capabilities (the ability to partition the data set into separate classes effectively), easy adaptation to different types of data and input structures, possibility of fuzzy output values (probability of a pixel belonging to a certain information class type) that can enhance classification accuracies (classification accuracies of fuzzy outputs are discussed in the Fuzzy logic section), and good generalization for use with multiple images. Land/water rasters created using neural networks are later used with GIS methods to extract deltaic shorelines. The disadvantages of the method are inconsistent results due to random initial weights, the requirement of obscure initialization values (e.g., learning rate and hidden layer size: the “black box,” phenomenon in which the user feeds in data and receives answers, and no access to the exact decision making process), slow training time of the network, and heavy computational demand to train the network for large datasets (Xie *et al*. 2008). For a detailed analysis of advantages and disadvantages of neural networks for remote sensing applications, the readers are referred to Jarvis and Stuart (1996) and Mas and Flores (2008). We can conclude from the literature that although the neural network method has several unique capabilities, it will become a useful tool in remote sensing only if it is made faster, more predictable, and easier to implement.

3.1.9 Decision Trees and Random Forest Classifiers

A Decision Tree is a tree-structure like flowchart (Friedl and Brodley, 1997; Figure 6). There are many different types of decision tree algorithms, e.g. Classification and Regression Tree Algorithm (CART; Denison *et al.*, 1998), C4.5 (Mazid *et al.*, 2010).

Decision Trees are easy to interpret, their internal workings are capable of being observed, making it possible to reproduce work, while making no statistical assumptions regarding the distribution of data (Hass and Bun, 2014). They are also computationally efficient (Friedl and Brodley, 1997), and perform well on large multispectral datasets (Zhang *et al.*, 2017).

One of the major problems with using decision trees is overfitting, especially when a tree is particularly deep (Friedl and Brodley, 1997; Pal and Mather, 2003). Over-fitting occurs when the tree is designed so as to perfectly fit all samples in the training data set, resulting in branches with strict rules of sparse data. This affects the accuracy when predicting samples that are not part of the training set (i.e. yields highly accurate output for the training data but low accuracy for test data).

Random Forest (RF) classifiers mitigate this problem well. First proposed by Breiman (2001), a RF is simply a collection of decision trees whose results are aggregated into one final result. Their ability to limit over-fitting without substantially increasing error due to bias makes them a powerful model. In a random forest, the number of trees in the forest (n estimators), and the maximum number of features to be used in each tree can be specified. However, one cannot control the randomness over which feature is part of which tree in the forest, and there is no control on which data point is part of which tree. Accuracy keeps increasing as the number of trees is increased but becomes constant at a certain point.

RFs can handle both high dimensional data and use a large number of trees where the key issue is correlation reduction between the random classification variables (ability to handle thousands of input variables without variable deletion) and they can be run efficiently on large databases. The RF algorithm can also detect outliers, which can be very useful when some of the cases may be mislabeled.

Random forests have been extensively applied to deltaic image classification and has resulted in improved classification accuracy compared to traditional methods, such as maximum likelihood (ML) and artificial neural network (ANN) methods (Adam *et al.*, 2012; Akar and Güngör, 2015). RFs outperform single decision tree algorithms (Gislason *et al.*, 2006; Khatami *et al.*, 2016). With this combination of efficiency and accuracy, along with very useful analytical tools, the RF classifier is considered very desirable for multisource classification of remote sensing and geographic data. That said, RFs are not immune to caveats; they can be time-consuming, difficult to construct and require greater computational resources in comparison to decision trees. In addition, since RFs deal with a number of decision trees, and the randomness of features within decision trees is uncontrollable, there is no way for the user to have a qualitative understanding of the behavior of the dataset to have an educated guess of the outputs, and therefore, has to take the output decision of the algorithm at face value.

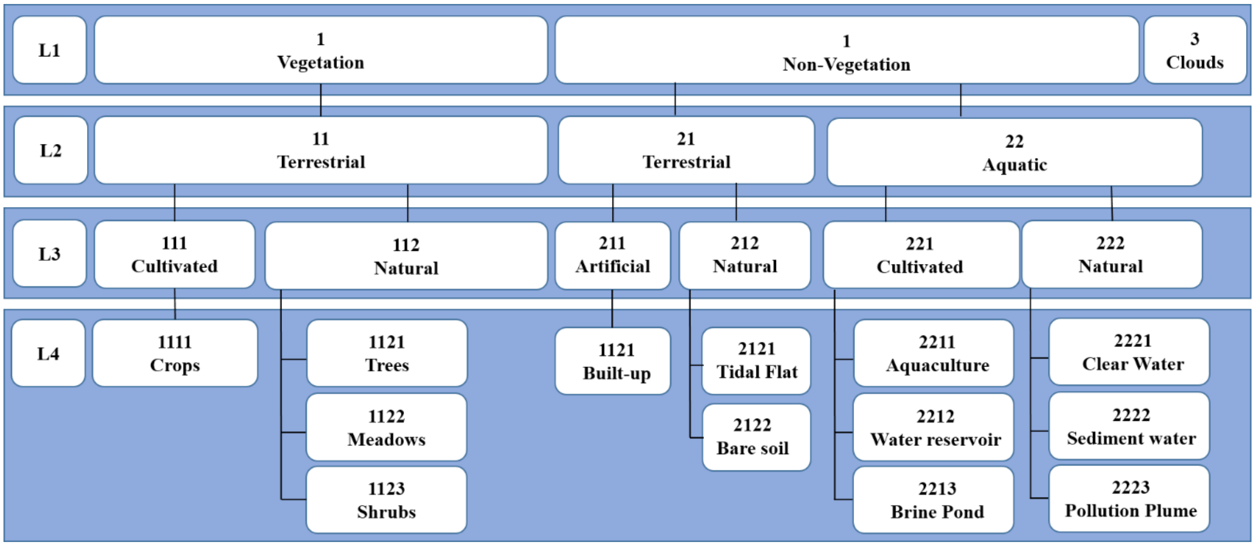


Figure 6: A decision tree to characterize different coastal features and isolate the shoreline

3.1.10 Bayesian Networks

Bayesian networks (BNs), also known as belief networks (or Bayes nets for short), are directed acyclic graphs (DAGs) belonging to the family of graphical models (Jensen, 1996). These graphical structures include nodes representing the various quantities, variables, or parameters that serve as input information, and edges between the nodes (the arrows connecting the nodes) representing probabilistic dependencies among the corresponding random variables. A node that is not connected shows a variable that is independent by other variables represented by nodes in the graph. In comparison to others, this is a relatively new method in deltaic-feature identification using remotely sensed imagery. Remotely sensed imagery can be used as input information (in contrast to the conventional field collected/modeled databases), and the conditional dependencies in the graph are often estimated by using known statistical and computational methods. The structure of a DAG in relation to evolution of a delta shoreline is illustrated in Figure 7.

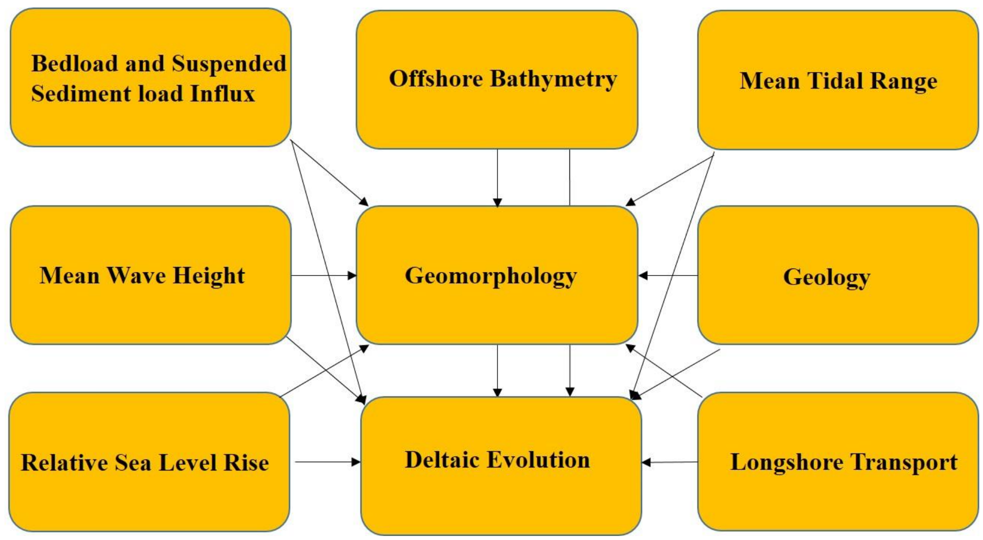


Figure 7: Bayesian Network to detect deltaic evolution. Black arrows indicate causal relationships linking the forcing factors and the response variable (deltaic evolution)

In Figure 7, the nodes represent random variables and are drawn as boxes labeled by the variable names. The edges represent direct dependence among the variables and are drawn by arrows between nodes. In particular, an edge from node "Mean Tidal Range" to node "[Deltaic] Geomorphology" represents a statistical dependence between the corresponding variables. Thus, the arrow indicates that a value given to variable "Geomorphology" depends on the value of variable "Mean Tidal Range". Given the conditional dependencies, BNs can be effectively used to represent knowledge about an uncertain domain (e.g. "Deltaic evolution") and algorithms can be created that allow for learning and inference through the use of a Bayesian network.

Often ANNs are compared to BNs due to their similarities in using directed graphs methods and are both used as classifier algorithms in problem solving. However, unlike ANNs the BN structure itself provides valuable information about conditional dependence between the variables. It is a visual representation of graph that is vertices and edges have meaning in comparison the ANNs where the network structure does not offer direct interpretations between nodes and can be difficult to interpret. Not many studies are found in literature which use BNs exclusively for deltaic feature detection (Table 2), primarily due to the large amount of supplementary data needed to setup such networks.

3.1.11 Support Vector Machines

A Support Vector Machine (SVM) is a machine-learning technique that is useful for multispectral and hyperspectral remotely-sensed classifications in which spectral separability between coastal land and water is difficult to ascertain due to lack of clear zonation between vegetation species, and mixed pixel effects. SVM differs from traditional classification approaches by identifying the boundary between classes in n-dimensional spectral-space rather than assigning points to a class based on mean values of class clusters (Heumann, 2011).

SVM creates a hyperplane through n-dimensional spectral-space that separates classes based on a user defined kernel function and parameters that are optimized using machine-learning (Figure 8). In other words, given labeled training data, the algorithm outputs an optimal hyperplane which categorizes new feature classes (Figure 8). In two-dimensional space this hyperplane is a line dividing a plane in two parts where each class lays either side of the hyperplane. By identifying the hyperplane that separates two classes rather than using the distance between class spectral means, SVM can produce a more accurate classification.

Several studies have demonstrated the great potential of SVM. Pal and Mather (2005) found that SVM outperforms maximum likelihood and artificial neural network using Landsat TM and is well suited for small training sets and high-dimensional data. Foody and Mathur (2006) found SVM outperforms discriminate analysis and decision-tree algorithms for airborne sensor data. Li *et al.* (2010) applied SVM to an Object-based Image Analysis (OBIA) with better results than standard fuzzy logic classification. Elhag *et al.* (2013) used Landsat TM and ETM+ imagery to map landcover in the Nile River Delta using SVM and Supervised classification approaches and showed that SVM showed higher classification accuracies. Thanh Noi and Kappas (2018) concluded that the SVM classifier on average outperformed the Random forest and kNN (K-nearest neighbor (unsupervised)) classifiers. Given the success in the literature (see examples in Table 2), we can conclude that SVM as the best individual classification technique for morphology change detection amongst pixel-based classification techniques.

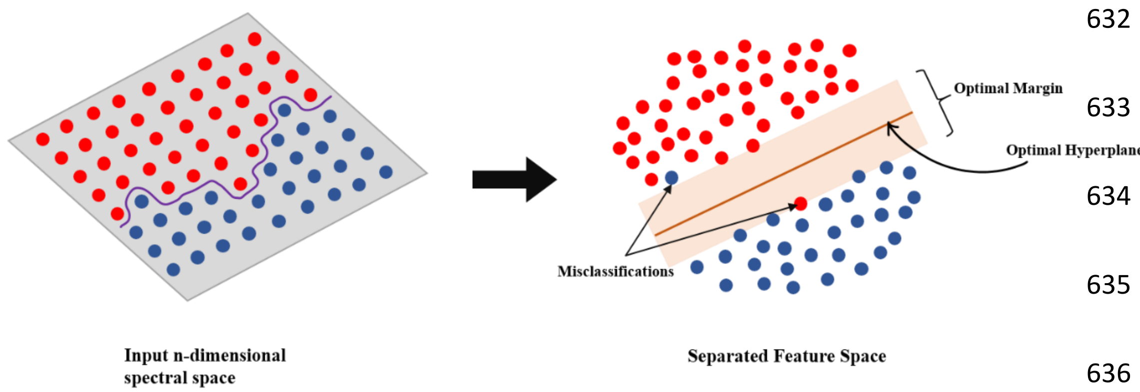


Figure 8: An Illustration of the SVM concept

3.1.12 Object-based Image Analysis (OBIA)

Traditional pixel-based image classification assigns a land cover class per pixel. All pixels are the same size, same shape and do not have any implicit connectivity with of their neighboring cells. OBIA, on the other hand, segments an image by grouping small pixels together into vector objects. The OBIA is a two–step process: segmentation and classification. Segmentation breaks up the image into objects representing land-based features. These segmented objects become the unit of analysis, from which spectral statistics, such as spectral band means and standard deviation, or spatial information, such as image texture, can be used in the second process; image classification. In image classification, according to the spectral, temporal and spatial response of land cover types in the objects, the corresponding bands and band combinations are selected, and their sensitivity is trained.

Object Based Image Analysis is conceptually simple and generic across sensors (Blaschke, 2010). The key benefits of OBIA relative to pixel-based methods include: (1) the possibility to incorporate user-defined scale, shape, and compactness parameters useful for creating objects with heterogeneous pixels (in the process of creating objects, scale determines the occurrence or absence of an object class, and the size of an object affects a classification result), in addition to spectral values of the input image layers (Blaschke, 2010); (2) smoothing some of the local variation within objects, which may reduce the salt-and-pepper noise and enhance classification accuracy (Kamal and Phinn, 2011; Kim *et al.,* 2011); and (3) accounting for the landscape hierarchy of patch, cover type and ecosystem structure by working with multiple object layers nested within each other at different spatial scales (Krause *et al.*, 2004). The approximation of ground entities and patches by image objects makes them more ecologically relevant and potentially more resilient to minor geospatial positioning and image registration error than pixel units (Yoshino *et al.*, 2014).

Drawbacks include spectral similarity of diverse classes due to homogenizing effects of moisture or dead vegetation signals, and dilution of fine morphological features which may reduce classification accuracy and the effectiveness of class discrimination (Kamal and Phinn, 2011; Yoshino *et al.*, 2014).

3.1 (B) Sub-pixel-based methods

Most classification approaches, as discussed above, are based on per-pixel information, in which each pixel is classified into one category and the land-cover classes are mutually exclusive. However, in the highly turbid coastal zone, waters are mixed with various materials including suspended particles, sediments and phytoplankton, and can often be classified as “land” in many conventional algorithms. In addition, classification accuracies decrease when there is more than one land cover type within a given pixel (Figure 9), making it a challenging task to correctly classify new land growth and shorefront with shoal waters.

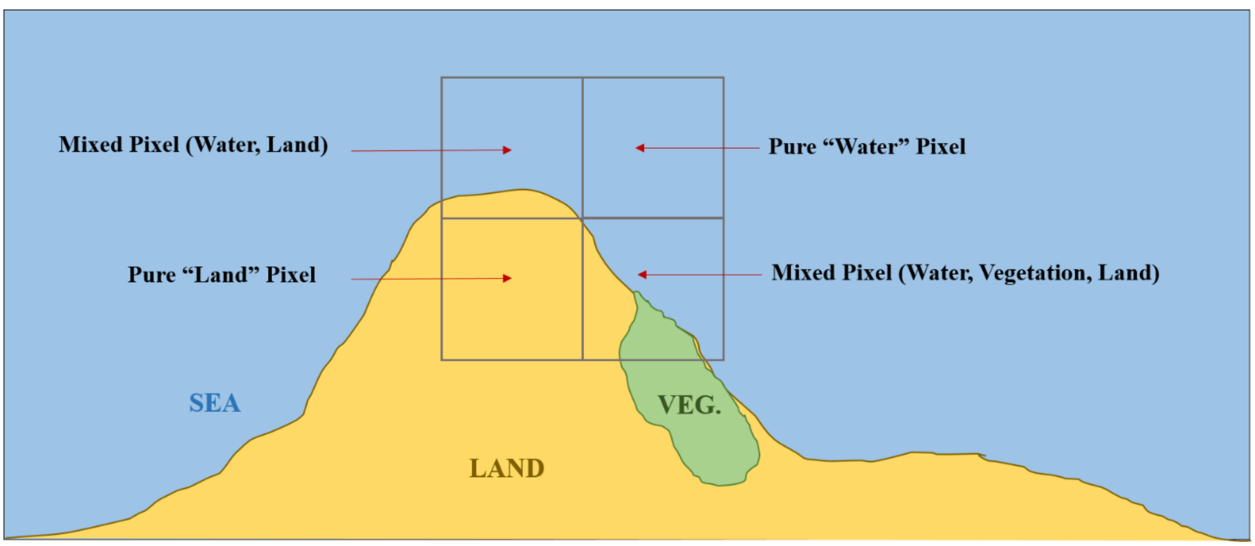


Figure 9: The case of the ‘mixed pixel’

A relatively young field in image analysis, and one that has gained traction over the past decade or so, Sub-pixel representations, provide the opportunity to extract information about the fraction of different classes within a mixed pixel (soft classification). Soft Classification approaches in general were shown to result in improved cartographic representations of transitional zones and heterogeneous landscapes (Frohn *et al.*, 2012; Wei *et al.*, 2008; Zhang, 2009). There are three main types of soft classification approaches used in delta morphology studies currently: Fuzzy Logic, Spectral Mixture Analysis, and Sub-Pixel Analysis.

3.1.13 Fuzzy Logic

A fuzzy classification technique is a probability-based classification rather than a hard classification. It was shown to be an extremely useful classification technique in deltaic regions where the identification of the shoreline is challenging due to the shallowness and turbidity of water, vegetative gradients, and dynamically changing waterline (Zhu, 2001). A fuzzy classification allows a pixel to have multiple and partial class memberships to accommodate the effects of mixed pixels. The conventional output of a fuzzy classification is a set of fraction images which indicate the relative coverage of the classes in the area represented by the pixel. If these predicted class covers could be located geographically within the area represented by the pixel, it would allow the boundary between classes to be plotted at a subpixel scale.

Fuzzy classification has advantages over conventional methods and improves drastically on the classification accuracies by fuzzy partitioning as the spectral space and retaining information otherwise would have been lost due to conventional partitioning and classifier training. Ghanavati *et al.* (2008) showed a better performance of fuzzy classification over maximum likelihood classification and also showed better discrimination of mixed and unmixed land use/land cover categories. It is also more feasible in integrating remotely sensed data and ancillary data (Zhang & Foody, 1998; Sha *et al*., 2008) such as digital elevation models, channel networks and climate data (Lu and Weng, 2007). However, fuzzy classifications can be very slow with long run-times during feature classifications when higher accuracies are sought after. This is because additional fuzzy rules have to be incorporated into the system, and algorithms need to be tweaked (since they do not use training data) to solve for complex deltaic environments.

3.1.14 Spectral Mixture Analysis

Spectral mixture analysis (SMA) enables the extraction of information about the surface materials present in a pixel. This is done by calculating the least-squares best fit for each pixel along mixing lines bounded by spectra of end-members and in this way accounts for each pixel's variation in the mixture composition (Ozesmi and Bauer, 2002). An end-member ideally represents a pure component of the mixtures present in the pixels.

The output of SMA is typically presented in the form of fraction images, with one image for each end-member spectrum, representing the area proportions of the end-members within the pixel. End-member selection is one of the most important aspects in SMA, and much previous research has explored selection/identification approaches (Mustard and Sunshine, 1999; Theseira *et al.*, 2003; Small, 2004).

Previous research has demonstrated that SMA is helpful for improving classification accuracy (Shimabukuro *et al.*, 1998; Lu *et al.*, 2003) and is especially important for improving area estimation of land-cover classes based on coarse spatial resolution data. Albeit its increased accuracy over other methods, SMA suffers from two major caveats of 1) not having potential end-members occurring in patches larger than the image resolution; there could exist earth features in smaller patches smaller than pixel dimensions. This makes the identification of an end-member for classification impossible and consequently be classified erroneously. 2) end-members not being truly constant within an image; there always exist a range of reflectance values for a particular end-member class that could result in overlap between different end-member classes. This could create a mismatch between the defined end-member and ground truth and yield misclassification results.

3.1.15 Sub-Pixel Analysis

Sub-pixel processing is defined as the search for specific materials of interest from within a pixel's mixed multispectral image digital number spectrum. This method has advantages over SMA and fuzzy classifications, because the overall composition of each pixel is not limited to a combination of already defined image classes (end-members). The steps in sub-pixel processing include signature derivation for a material of interest and classification of each pixel identifying the fraction of material of interest present. Therefore, for each material a separate classification must be done. The fraction image pixel values vary from 0.0 to 1.0 (Ozesmi and Bauer, 2002). This specific technique of sub-pixel analysis in deltaic environments was the least used technique in the reviewed literature.

3.1.16 General Concerns about Techniques used in Two-Step Change Detection

The 15 techniques used in Two-Step Change Detection for delta morphology analysis described above, although commonly used, share some inherent limitations. One limitation is that since separate classifications are carried out on two different satellite images before detecting the deltaic change, the accuracy of the change map typically will be at best the multiplication of the accuracies of each individual classification for each date (Serra *et al.*, 2003). This is a concerning problem as this error can be significant at times, especially when multiple time steps are compared. Also, when the analyses include utilization of imagery from longer archives (i.e. use of different Satellites even in the same constellation; e.g. Landsat MSS, TM etc.), it is inevitable that different data extraction and classification algorithms needed to be used to infer deltaic features (due to the variability of spectral resolution of bands). This process, in addition to the caveat mentioned above, carries the distinct disadvantage of having uncertainties occurring due to differing classification/extraction algorithms. Thus, the two-step detection will incur an additional step of quantifying of uncertainties.

Furthermore, Two-Step Change Detection, since it requires the production of at least two different maps, can be operationally complex and computationally intensive (especially on high resolution multispectral imagery covering large areas). Therefore, the use of said methods to produce time series of change-maps can be difficult and expensive. Multi-temporal image comparison techniques/One-step change detection techniques (discussed below) were, in part, developed to alleviate these limitations.

3.2 Classification Techniques used in One-Step Change Detection

3.2.1 Image Differencing/Layer Arithmetic

In this technique, spatially registered images from different times are subtracted, pixel by pixel, to produce a layer which represents the change between the two. This procedure yields a difference distribution for each band (i.e. a histogram). In such a distribution, pixels of small radiance change are distributed around the mean, while pixels of large radiance change are distributed in the tails of the distribution (Mas, 1999). A critical element of the image differencing method is deciding where to place the threshold boundaries between change and no-change pixels displayed in this distribution.

Although Image Differencing is a widely used technique for change detection and has been used in river deltas of different geographical environments (Table 2), interpreting the difference image can be difficult because different input values can have similar output results after subtraction (e.g. input pixel values of 190 and 150 can have the same result of 40, as inputs of 100 and 60, after subtraction), and also since the original pixel value information is not retained for further investigations (Cohen *et al.*, 1998). The mathematics of typical image differencing is shown in Figure 10 below.

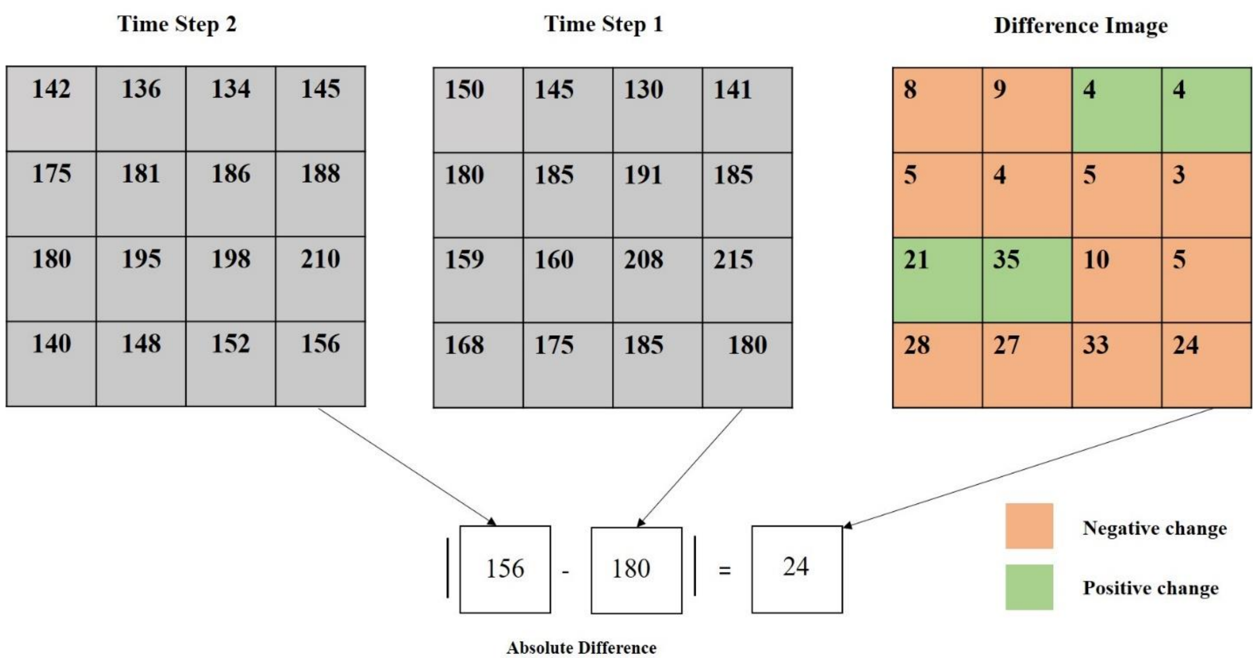


Figure 10: Image differencing workflow between typical rasters. The values are arbitrary values used for illustration purposes.

3.2.2 Change Vector Analysis

Change Vector Analysis (CVA) is an enhanced version of band differencing. It detects changes above a selected threshold value to generate a binary image of change and no-change pixels (Singh and Talwar, 2013). A change vector can be described as an angle (vector direction) and a magnitude of change between two different time instances from multi-spectral satellite data (Civco *et al.*, 2002). A decision on change is made based on whether the change magnitude exceeds a specific threshold. Once a pixel is identified as changed, the direction can be examined further to determine the type of change. The type of change is often identified using the angle of the vector in two spectral dimensions (Chen *et al.*, 2003). Although initially developed for only two spectral bands, modifications to CVA enable its use to any number of spectral bands (Bayarjargal *et al.*, 2006).

In addition to providing the direction of change, which is unparalleled to other techniques discussed, CVA also has the capability of avoiding cumulative error in image classification of an individual date and processing any number of spectral bands simultaneously to retrieve maximum "from-to" type information. However, like other radiometric change approaches, CVA also has several drawbacks that limit its use. These include a strict requirement for reliable image radiometry. CVA is based on pixel-wise radiometric comparison and so the accuracy of image radiometric correction (for alleviating the impacts caused by disturbing factors such as different atmospheric conditions, solar angle, soil moisture and vegetation phenology, etc.) is more critical for CVA than for spectral classification approaches. Another drawback is a lack of automatic or semiautomatic methods to effectively determine the threshold of change magnitude between change and no-change pixels (Chen *et al.*, 2003).

3.3 Ensemble Classifications

Different image classification methods, such as parametric classifiers (e.g. maximum likelihood) and non-parametric classifiers (e.g. neural networks, decision trees), have their own strengths and limitations (Tso and Mather, 2001). For example, when sufficient training samples are available and the features in a dataset are normally distributed (distribution in space; among pixels), a maximum likelihood classifier (MLC) may yield an accurate classification result. In contrast, when image data are anomalously distributed, neural network and decision tree classifiers may demonstrate a better classification result (Lu *et al.*, 2004).

Ensemble (Hybrid) classification methods combine the strengths of multiple classification approaches. They can be valuable for river delta studies because of how they effectively address the complex variability in spectral responses of shoreline environments. Ensemble classifications can be classified into two approaches: 1) classifying a single image of a particular time step and then comparing it with an image of a different time step (classified using the same techniques or otherwise), or 2) directly comparing between two timestamps. The direct comparison between time steps is often expressed as a layer arithmetic operation to identify changed elements (locating change through e.g. CVA), followed by a supervised or unsupervised direct classification of the changed features (Lu *et al.*, 2004). Previous research has indicated that the integration of two or more classifiers provides improved classification accuracy compared to the use of a single classifier (Warrender and Augusteihn, 1999; Steele, 2000; Huang and Lees, 2004; Khatami *et al.*, 2016). In an effort to not duplicate studies and maintain the succinctness of the document, the readership is reverted to sections discussed above (3.1.1 – 3.1.15; 3.2.1 and 3.2.2) where instances of ensemble classifications can also be found. A note of caution when applying ensemble classifications is that the uncertainties occurring from different techniques have to be quantified and factored into accuracy calculations of feature extractions, as they can be significant depending on the methods used and the number of time steps of satellite imagery processed.

As evident from the discussion in sections 3.1-3.3, sub-pixel-based classifications tend to yield better results than pixel-based classifications. However, sub-pixel-based methods can be computationally expensive, and algorithm development can be time consuming. Thus, the choice of a sub-pixel-based algorithm is a trade-off between how complex the deltaic environment is, how big the river delta is (i.e. is the value of a pixel significant in comparison to the size of the delta?), and what is the time span of the delta change analysis (are multiple image time steps involved which could compound uncertainties). In addition, since there is also the problem of compounding error resulting from classification techniques of different time steps, development of algorithms to detect sub-pixel heterogeneity can be worthwhile if a one-step change detection method, even pixel-based (e.g. image differencing. CVA), can achieve comparable results as sub-pixel algorithms.

4. Other Delta Morphology Change Indicators

Section 3 of the manuscript focused on one delta morphology change indicator: the shoreline. The discussion of all other environmental indicators in one section is due to that fact that the number of studies pertaining to every other environmental indicator was markedly less than those for deltaic shoreline change studies. We attribute this to two reasons 1) research interest: more attention is given to how deltaic landmass available for humans evolve over time (governed by the shoreline), and 2) methodological challenges: difficulty for classification algorithms to distinguish between spectral characteristics of these specific deltaic features and the surrounding terrain features. The shoreline, on the other hand, even with its own complexities at the land-sea margin, is relatively easier to detect, as changes in spectral characteristic between land and sea are comparatively prominent. Possible pathways to address these less-researched environmental indicators are discussed as future directions in section 5. The following sub-sections will discuss studies with regard to other deltaic morphology change indicators. The importance and role of these indicators in delta morphology change detection is summarized in Table 1.

4.1 Meander Belts

Lateral migration as a response to variations in river flow and sediment discharges is associated with erosion of the stream bed or channel bank and can cause many geomorphological and river management problems on a delta (Le *et al.*, 2006). Mathers and Zalasiewicz (1999) used a combination of filtration and contrast stretching on Landsat TM imagery to map and classify Meander Belts of the Red River in the Red River Delta in Vietnam. Yang (1996) and Yang *et al.* (1999) used Manual Digitization and Band Ratioing/Manual digitization on Landsat MSS and TM imagery to identify channel shifting change (Channel Migrations), channel geometric change (Channel length and width) and channel pattern change (braiding, straight, slight meandering) of the Yellow River in the Yellow River Delta. Seker *et al.* (2005) studied meander migrations of the Filyos River in and upstream of the Filyos delta, Turkey (Figure 11) and Ghanavati *et al*. (2007) used topographic maps and Landsat TM and ETM+ imagery to detect channel migrations in the Hendijan River delta, Iran.

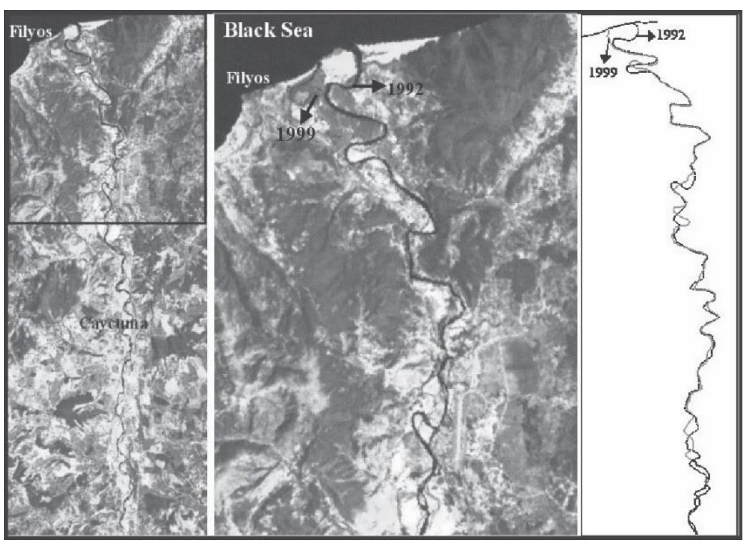


Figure 11: The meandering of the Filyos River through time observed using satellite imagery. Source: Seker *et al.* (2005).

4.2 Crevasse Splays, Channel Avulsions and Distributary Networks

Syvitski *et al.* (2012) used SRTM (Shuttle Radar Topography Mission) interferometric synthetic aperture radar (InSAR) data to study zones of nodal avulsions in 33 lowland floodplains (inclusive of deltas). Li *et al.* (2014) used Landsat MSS and TM imagery, and Li and Bristow (2015) used QuickBird-2 and WorldView-2 imagery to monitor flood-induced river morphology changes and to study splay development morphology respectively in the Río Colorado river delta in Salar de Uyuni, Bolivia (Figure 12). Mathers and Zalasiewicz (1999) used Landsat TM with the integration of geological data to study tidal creeks, channels, anastomosing rivers in the Red River Delta, Vietnam. Isikdogan *et al.* (2015) proposed an algorithm to automatically extract the channel networks from satellite imagery where water and non-water pixels have the greatest spectral contrast, and in an innovative use of high resolution google earth imagery, Gugliotta *et al.* (2019) obtained channel network widths and sinuosity of five deltas (Fly, Yangtze, GBM, Irrawaddy, and Mekong).

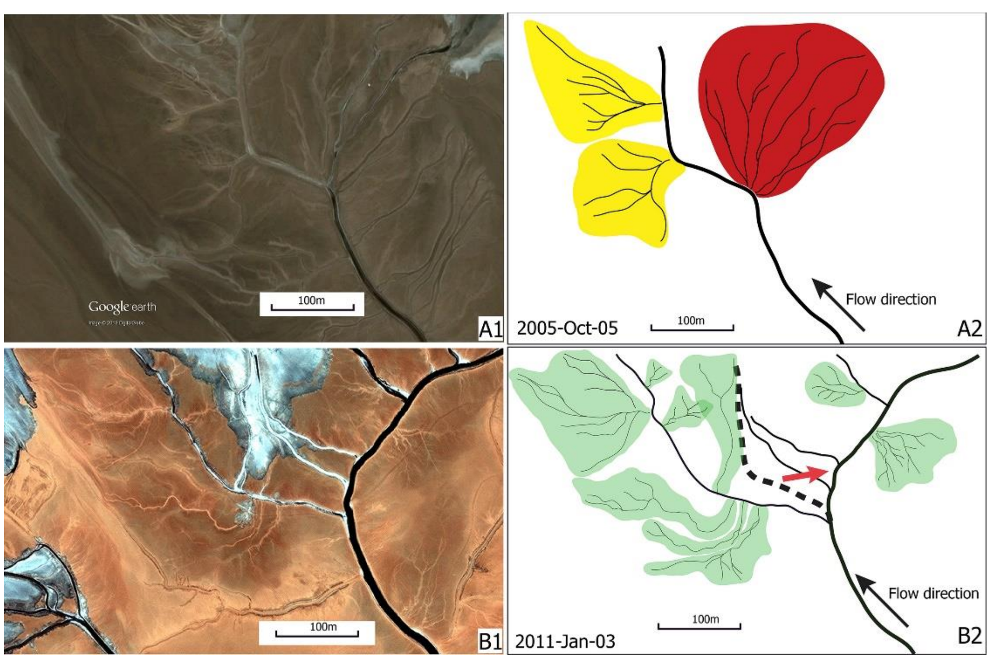


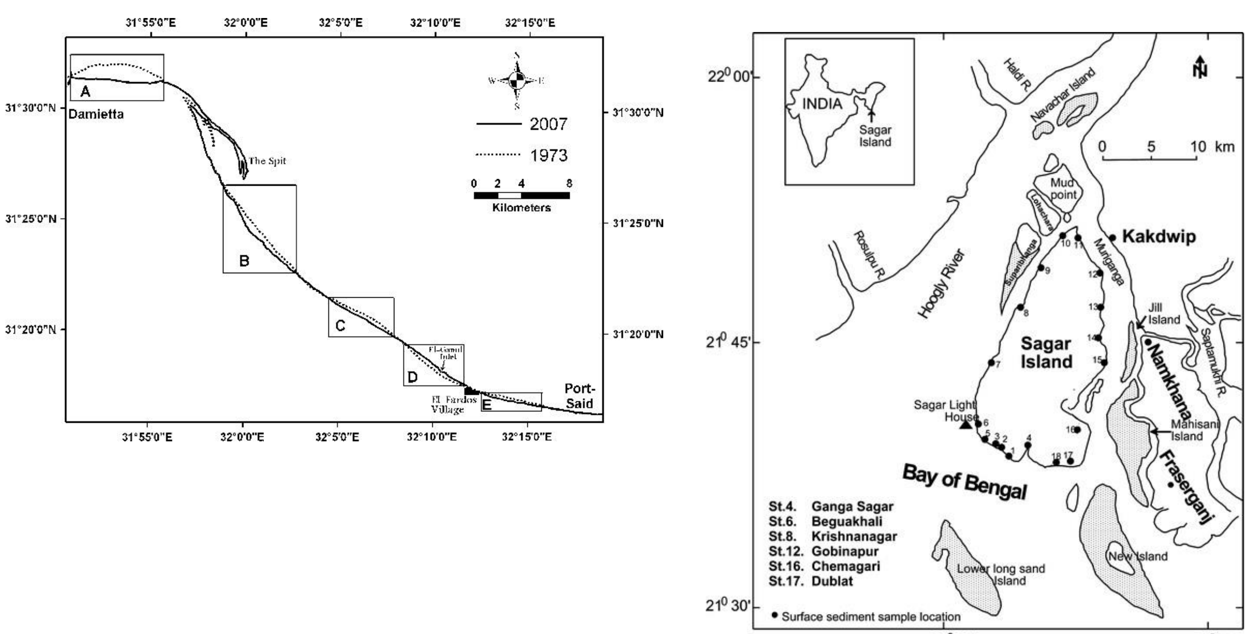
Figure 12: Crevasse splay-led avulsion in the Salar de Uyuni, Bolivia. A1 and B1: The same region observed from Quickbird (A1) and Worldview-2 (B1) satellites at two different times; A2 and B2: Line drawings, main river channel is demarcated by the thick black line. A2: yellow splays represent Inactive Crevasse Splays; red splay demarcates the site where avulsion occurs. B2: green splays represent new crevasse splays. Dashed line indicates river channel before avulsion. The arrow shows the channel shift after avulsion. Source: Li and Bristow (2015).

Studies of splays, avulsions and channel networks is particularly challenging in coastal deltas due to low topographic gradients, the presence of features such as sediment plumes, and the wide range of scales over which channel features are present. Channel networks identified in most of the studies were as good as the moderate resolution of the satellite imagery used. In addition, robust channel extraction methods would ease monitoring coastal areas and analyzing deltaic response to anthropogenic and natural forcing over large spatial areas and long temporal intervals. The role of higher resolution satellite imagery in better identifying these deltaic features and the need for more robust deltaic feature extraction methods based on these better platforms is discussed in section 7.

4.3 Barrier Islands, Beach Spits, and Mouth Bars

Frihy *et al.* (1998) used Landsat satellite data to assess the evolution of the coastal spit and changes in the lagoon margin and contiguous barrier islands in the Damietta Promontary of the Nile River Delta. Nandi *et al.* (2016) used Tasseled Cap Transformation on Landsat MSS, TM, ETM+ while Gopinath and Seralathan (2005) used image differencing on satellite data of the Indian Remote Sensing Satellite-IC to monitor changes of Sagar Island, the largest mouth bar of the Ganga-Brahmaputra-Meghna (GBM) delta. Demers *et al.* (2015) used RADARSAT-2 C–band and optical satellite data to map the shoreline of islands of the outer Mackenzie Delta using

Object Based Image Analysis. A common problematic are highlighted in these studies was detecting these morphological features using medium to coarse resolution imagery. Better pixel resolutions in comparison to the scale of deltaic features (Figure 13) were shown to be an area of improvement for better feature detection. In addition, the detections were heavily impaired by the sediment plume in the delta nearshore environment. The necessity of data mining and sub-pixel analyses was apparent. We discuss these shortcomings and possible pathways forward in detail in section 7; Future Directions.



(A)

(B)

Figure 13: (A) The shoreline position change through time (1973 and 2007) between Damietta and Port-Said of the Nile River Delta. A prominent beach spit is visible between locations A and B. Source: El-Asmar and Hereher (2011). (B) Location of The Sagar Island, the largest barrier Island in the Ganges-Brahmaputra-Meghna Delta. Ground control points were collected at each sampling station to calibrate satellite data. Source: Gopinath and Seralathan (2005).

5. Synthesis and Applications

5.1 Machine Learning

One of the major insights stemming from this literature review is that sub-pixel-based methods tend to yield the highest accuracies among all the discussed methods in morphology change detection, while machine learning (ML) techniques perform relatively better (contingent upon good training data, and knowledge and skill of the algorithm developer) than conventional pixel-based techniques (band ratioing, density slicing). The former is a straightforward conclusion given that sub-pixel-based methods inspect details within the constraints of a pixel to elucidate information about the land surface which is otherwise impossible through pixel-based methods; higher level of inspection within a pixel will yield greater amounts of detail.

Perhaps more interesting is the insight that ML techniques (e.g. ANNs, Bayesian networks etc.) perform better than conventional methods, given that they both work at a pixel-level. It is also found that using a combination of ML techniques with others (another ML technique or other conventional ones) was shown to yield very high accuracy and utility in morphological feature classification. Thus, it is worthwhile examining why ML techniques perform well in deltaic environments, so we could better understand and harness their strengths to developing data mining algorithms in under-studied deltaic regions of the world, and even solve image classification issues in other sub-disciplines of satellite remote sensing.

The reasons for the success of ML techniques in case studies in the studied literature lie in the complexity of the deltaic system itself. One of the fundamental characteristics of a complex system is that classification results are non-linear stemming from the heterogeneity in the system (a spectral reflectance of *x* denoting water at one location, might be a mixture of mud, water and vegetation debris, at another). A conventional algorithm is designed to classify the system using a simple succession of steps subject to simple conditions. ML algorithms, on the other hand, have the ability to identify complex relationships through the testing of a very large number of possibilities. Typically, the algorithm runs multiple experiments of classification on the primary image data before arriving at a final decision output. The outcome of the second experiment will not be the same as the first, and the final result is thus an ensemble of the two. ML algorithms work on the principle that it generally approximates the truth instead of aiming to find it exactly, in comparison to conventional methods, which in a complex domain such as a delta, can lead to lowered accuracies due to misclassification. The approximation of the truth of ML techniques, thus, also provide a measure of uncertainty, and can act as platforms for other types of research to build up on, which can later-on be incorporated into the decision-making process. Secondly, in a ML algorithm, many other factors related to morphology change are considered before assigning a label to a particular image pixel (e.g. see Figure 7 of how a Bayesian network solves for a deltaic evolution). This provides ancillary data (remotely sensed or not) of the deltaic environment, which improves the classification accuracy of the algorithm.

We understand that not every researcher engaged in remote sensing possesses the skills of developing complex ML algorithms. Therefore, we would also like to make a point that although ML algorithms are favorable, a combination of conventional methods in an ensemble could also lead to good classification accuracies.

What type of algorithm should one use for delta morphology detection? Is it worth the effort of going the entire distance of developing highly accurate, complex ML algorithms when, comparable results can be achieved through already existing conventional remote sensing techniques? The answer to these questions, in our opinion, depends on several factors. The most important is the study domain of interest. For example, the Damietta and Rosetta Promontaries of the Nile River Delta, Egypt (which are made of the Damietta and Rosetta branches of the Nile River, respectively) are cuspate shaped, with straight forward land-sea margins (Figure 14a). Due to the clear difference in spectral signatures the deltaic land can be clearly distinguishable from the ocean. On the contrary, the Ganges-Brahmaputra-Meghna (GBM) delta in India/Bangladesh has intricate coastal features on the land-sea margin (Figure 14b). The extensive anastomosis of channels, huge volume of sediment output, complex vegetation gradient, presence of barrier islands, mouth bars and lagoons at the land-sea interface complicates the detection of morphological features.

(a) (b)

Figure 14: The comparisons of shorelines between the (a) Damietta Promontary of the Nile River Delta and the (b) Ganges-Brahmaputra-Meghna Delta

Therefore, it would be prudent to use a combination of conventional techniques to monitor the Nile, in order to utilize available resources (time, user-skills) effectively rather than going the extra step of deep algorithm development, which might be very well the case for the GBM delta. It is therefore of utmost importance to have an understanding of the complexity of the study domains prior to the development of research methodology. It is also important to be informed how of data-intensive and computationally costly these algorithms are. For example, a Bayesian network might be significantly better than a simple band ratio, but is it worth the trade-off of time that one would invest to develop the algorithm and the amount of ancillary data (which might need to be purchased and pre-conditioned) that is required to arrive at a relatively uncomplicated feature extraction?

5.2 Radar Imagery

Literature about the use of Radar imagery for deltaic morphological feature detection was minimal compared to optical platforms. This is likely due to a combination of factors. The first is the premium access that was needed for almost all radar archives until very recently. Research proposals on intended projects had to be submitted to data providing agencies, and on most occasions, imagery had to be purchased. Secondly, unlike the lengthy activation periods of optical platforms (e.g. Landsat, since 1972) the discontinuation of radar platforms within a short period of time has led to short archival length of radar imagery which consequently resulted in difficulty in monitoring deltaic changes over time. Thirdly, skilled photogrammetric operators are needed to process and analyze radar imagery, and these skills are not ubiquitous. Fourthly, and most importantly is the utility in distinguishing on-land deltaic features such as crevasse splays and avulsions, especially in complex deltaic regions. Although radar imagery is well utilized in shoreline delineation (see examples in Table 2), there is no conclusive evidence that suggests that Radar imagery performs well in comparison to optical imagery in recognizing on-land deltaic features. Thus, given the choice between optical and radar platforms, the rational selection seemed to be optical imagery over the years in most cases. However, with open accessibility policies to radar archives through the Copernicus Program of the European Union, Alaska Satellite Facility and the Japan Aerospace Exploration Agency (JAXA), and training programs/Webinars offered by NASA, European Space Agency and other private institutions, opportunities in relation to feature detection are expected to open into the future.

6. Intercomparison of Delta Morphology Feature Extraction Techniques

One of the more important insights that we draw from the summation of studies is that the review of literature revealed no clear clustering of a particular set of technique(s) that could be used for feature extraction for a particular type of delta (e.g. river-dominated vs. tide-dominated). One or two given techniques which were used to extract a particular morphological feature (e.g. shoreline) of a particular type of delta (e.g. river-dominated delta) was not necessarily ideal for a river dominated delta elsewhere on the earth. This is understandable as deltaic morphology dynamics are driven by many other location/climate related factors (e.g. inherent variability in rainfall, soil minerals, growing cycle phases of vegetation) that make the identification of morphological features even using the same technique complex. We noted that there were not enough comparison studies which 1) compared multiple techniques at a given case study, nor 2) comparisons of even one or two techniques across multiple case studies in different geographical regions of the world. The notion of which technique(s) would be the most appropriate for a given deltaic region would be immensely important for potential future research as these could be used to infer on how to fine tune algorithms to compensate for environmental noise, and subsequently accurately detect deltaic landmass evolution over time. This will help us infer why particular techniques underperform in differentiating earth features in different geographic regions of the world, enabling deeper investigation into some of the inherent problems of particular techniques and provide a platform for their improvement. In addressing this niche, we evaluated 7 techniques on 10 different river deltas (Amazon, Chao Phraya, Burdekin, Brahmani, Po, Danube, Ebro, Han, Irrawaddy, Colorado) globally, belonging to different river delta types (i.e. river-dominated, tide-dominated, wave-dominated) and representing the different Köppen climate classes.

Five conventional and two ML methods were compared. The conventional methods are: 1) Modified Normalized Difference Water Index (MNDWI), 2) Normalized Difference Water Index (NDWI), 3) PCA analysis, 4) Unsupervised Classification, and 5) Supervised Classification)]. The ML techniques used are: 6) Random Forest Classifier, and 7) Support Vector Machine)]. These seven techniques were selected as they were the most used as per our review. All were compared against hand-digitized vectors (used as a reference baseline) of Landsat-OLI 2018 imagery for the 10 case study deltas (the number of case studies were constrained by the availability of sufficient training data for ML techniques). The accuracy of different indicators of morphology (shoreline, beach spits, mouth bars etc.) were evaluated against the hand-digitizations based on two parameters: a) the continuity of the technique-derived vector to the reference baseline, and b) Proximity of technique-derived vector to the reference baseline. A new robustness index (R) was developed which joins both metrics:

$$R = \frac{L_E * 100 / L_R}{D_{EA}} \tag{1}$$

where L_E is the length of the extracted shoreline, L_R is the length of the real shoreline, and D_{EA} is the averaged perpendicular distance between the extracted and real shoreline. The R index value increases as the shoreline extracted by a given method is closer to the real shoreline in length, whereas robustness decreases as the extracted shoreline is farther away from the real shoreline. Best and worst performing techniques of each delta are summarized in Figure 15 below.

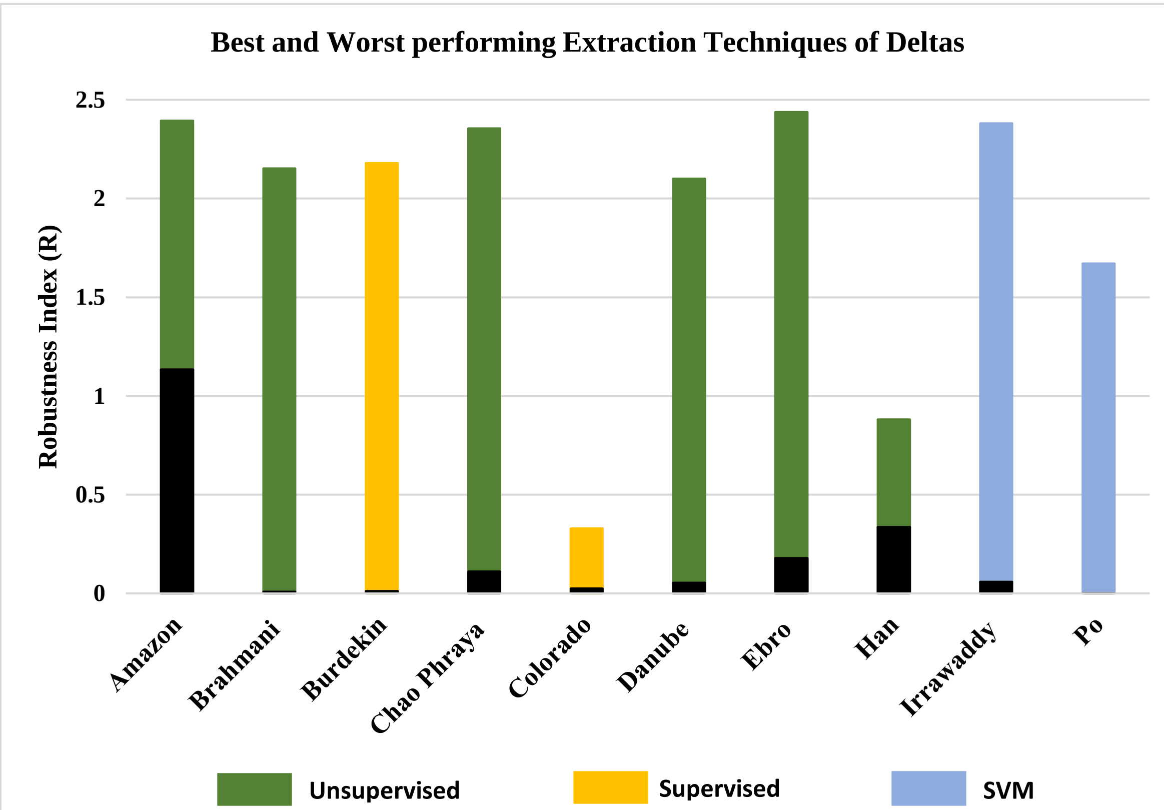


Figure 15: A summary of the best and worst performing techniques of the sample deltas.

Analyses show that, except for two cases (the Po and Irrawaddy Deltas), Unsupervised and Supervised Classifications performed the best across all morphology indicators (e.g. beach spits, tombolos, shoreline) (Figure 16). For the Po and Irrawaddy Deltas, the Support Vector Machine algorithm performed the best. PCA ranked the lowest among the techniques for all the deltas, and we attribute these low PCA scores to the non-capture of boundary line land-sea pixels as ‘noise’, from the first few principal components during the transformation process.

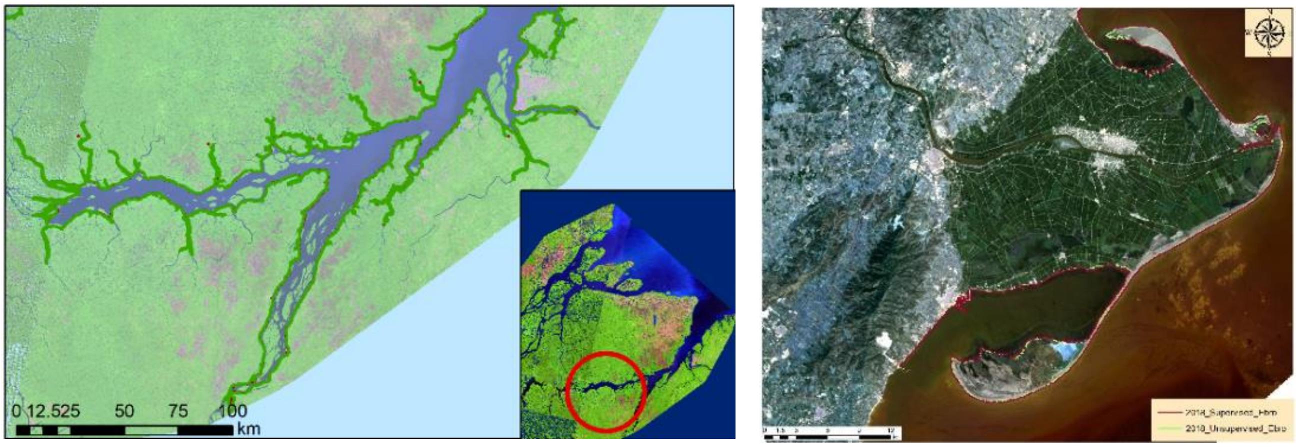


Figure 16: Algorithm performance on delta morphology indicators. *left*: the detailed extraction of extensive channel networks of the Amazon river subsequent to unsupervised classification. *Right:* A comparison of vectors of shoreline and beach spit extractions between unsupervised (green) and supervised (red) of the Ebro delta.

However, when the performance of all the techniques were summarized (Table 1) and analyzed for robustness, we find that Unsupervised Classification yielded the best performance on average. A nonparametric ANOVA showed that when all river deltas were considered, Robustness (*R)* values of Unsupervised Classifications were significantly outperforming all the other techniques. SVM, Supervised Classifications, and Random Forest Classifications did not show a significant difference ($\alpha = 0.05$) between each other. The two ratioing techniques' performance also did not have a significant difference between each other ($P=0.79$; $\alpha = 0.05$). All other techniques had significant differences with PCA (Table 1).

Table 3: The ranges of the percentage lengths of extracted shorelines, their average distances from the real shoreline and mean robustness values for each technique, for the entire suit of deltas (10) analyzed.

Technique	*Range of L_E (%) (Median in parenthesis)*	*Range of D_{EA} (m) (Median in parenthesis)*	*R* mean
Unsupervised	78-100 (98)	40-239 (45)	1.72
SVM	36-99 (79)	42-340 (60)	1.17
Supervised	56-99 (87)	45-246 (87)	1.14
Random Forest	45-97 (76)	45-471 (78)	0.95
MNDWI	23-79 (50)	78-587 (229)	0.32
NDVI	29-70 (52)	105-623 (172)	0.31
PCA	4-84 (24)	75-2668 (427)	0.19

We did not observe clustering of techniques around delta types, nor between deltas in specific Köppen climate classes. However, it must be noted that these are only a small sample of deltas from each delta type and Köppen category. It was interesting to note how although past literature showed that support vector machines (SVMs) as the best among pixel-based classifications, our comparisons yield mixed outcomes (SVM performing best in only 2 cases out of the 10, and second ranked in all other cases). We attribute this to two reasons: 1) classification algorithm accuracies depend vastly on the resolution of the satellites, and 2) the training data that we used for the SVMs were derived from other satellite products (of higher resolutions than Landsat). The literature review reflects a variety of resolutions and sources as opposed to our use of 30 m Landsat imagery for all the case studies. On the other hand, some studies used in-situ field measurements as training data which likely led to higher classification accuracy. However, given the almost similar accuracies of unsupervised classification and SVM, we recommend the prior (as SVMs require good training data and takes time for algorithm development) for deltaic feature detection based on Landsat imagery.

In a synergistic study, Munasinghe et al. (under review) evaluated 5 conventional remote sensing techniques (the same as used in this study) on 44 global river deltas worldwide in an attempt to infer on the performance of techniques in shoreline extraction in different types of deltas (River, Tide, Wave-dominated) in different geographic/climatic regions. A major goal of that study was to draw common generalizations and working behaviors of techniques around well-known types of deltas and apply them to lesser studied, data sparse regions. Results showed that Unsupervised classification yielded the best performance for the majority of the deltas (35 of 44) whilst supervised classification yielded the best for the remainders (9 of 44). They also found that extraction accuracies were higher in wave dominated deltas, lower for tide-dominated deltas, and moderate for river-dominated deltas. Reasons were attributed to the alongshore sediment transport processes of the wave-dominated deltas, resulting in sandy shorelines which has higher contrast with the less-muddied ocean making it easier for land-water boundary identification. In comparison, sediment-rich murky waters in the nearshore environment governed by the intertidal oscillations in tide-dominated deltas provided less contrast with land. Hence reduced extraction accuracies. Based on results of both these studies, we recommend the use of Unsupervised Classification as a first order extraction technique for data sparse deltas or previously unstudied deltaic regions.

7. Future Directions

Based on our evaluation of the literature, we see four areas which we deem most opportune for future development:

Direction 1: Utilization of higher resolution imagery and developing better sub-pixel data mining techniques

An important aspect that we recognized earlier was that, compared to shoreline changes, there was a dearth in the number of studies that focused on other environmental indicators of delta morphology change. This was explained by the fact that the shoreline governs the effective landmass that is suitable for human use and is prudent to know the progradation and degradation of a delta against sea level rise and fast changing climatic conditions. Consequently, shoreline change studies, evidently, seem to have greater weightage and research merit than other indicators. We, however, would like to bring out a different perspective to the problem in recognizing that technological limitation is also an important governing factor of these disparate numbers. Specifically, the spatial resolutions of earth observing satellites that are used to detect environmental indicators of river delta morphology change.

Detecting the shoreline of a delta, although as described earlier is quite complicated, can be performed relatively well with imagery with moderate spatial resolution (in the range of 30 – 250 m). On the other hand, detecting crevasse splays, channel avulsions and anastomosis of channels with a high level of accuracy, especially in smaller channels and topographically challenging regions, require very high-resolution satellite imagery (below 10 m). The problem is exacerbated if these changes are required to be detected in particularly small deltas, as the background noise from surrounding, non-deltaic, features can heavily influence these analyses.

In the last decade, we experienced a great increase in the availability of higher resolution satellite imagery, primarily through commercial space programs (e.g. Planet Labs, Airbus Defense and Space, Inc.). These sub-meter resolution platforms could be instrumental in detecting intricate deltaic features. Striving for higher resolutions, however, comes at a cost. With an exception of programs that provide conditional access to high resolution satellite archives (e.g. Planet labs), most of these platforms are payment-based, and imagery acquisition could be a significant proponent of the project budget. Costs also include data storage and purchase and maintenance of high-powered computational systems. Due to exorbitant costs, and also due to limited archival length (since most of these platforms are new, the length of their archives is not sufficient for delta change studies), the usage of higher resolution platforms is still limited in deltaic research. However, it can be expected that, as time progresses, the use of these platforms will increase dramatically.

In the meantime, fusion of high and medium resolution imagery for detecting fine resolution deltaic features is one promising way forward. Image fusion and the consequent overall increase in resolution presents a solution to another problem: presence of mixed pixels in shoreline classification. As described earlier, this issue has been recognized as a major problem influencing the accuracy of remote-sensing image classification (Liu *et al.*, 2016). Theoretically, with improvements in imagery spatial resolution, the number of mixed pixels will be greatly decreased (Wu, 2009).

There is also great potential in developing novel data mining algorithms, especially sub-pixel algorithms (which have historically shown success in the literature) that can be used with already existing moderate spatial resolution platforms. Examples of such algorithms, which were recently applied to delta morphology studies, include the grid-based colocation pattern mining technique (Sainju and Zhang, 2017), Spectral Unmixing Algorithm Based on Distance Geometry (Pu *et al.*, 2013), and the use of colorimetry to estimate the proportion of classes in mixed pixels (Suresh and Jain, 2018). Finding solutions to sub-pixel information will not only help advance morphological science forward but could also provide great impetus to the studies that will be forthcoming using high resolution satellite imagery.

Direction 2: Use of automated pattern recognition techniques, universal applicability and algorithm transferability across platforms

Although there exist several manual/semi-automated methods to extract information from satellite imagery as discussed in the sections above, we see great advantages in extraction of information though automated techniques for change detection which could reduce the errors due to operator bias and more efficiently partition and recognize patterns and relationships in datasets.

In this context, we think that “Smart Data Discovery - the idea of automating the identification of patterns and trends in large data sets” (Sallam *et al.*, 2017) - can play an important role in feature extraction from satellite big data. Smart data discovery is currently used increasingly in the business intelligence sector in making informed market decisions (Sallam *et al.*, 2017). We think however, that there is great potential for this technique in the domain of satellite remote sensing to prepare and cleanse data more intelligently, automatically find hidden patterns and correlations in data, especially where traditional and even semi-automatic machine learning techniques are expensive, difficult and time intensive to implement.

Algorithms that we develop also need to be near-universally applicable. Localized algorithms which work perfectly in one particular region or for a particular size and type of delta often do not perform well in other locations and is thus of relatively limited use elsewhere. To the holistic study of Earth’s geomorphology and its evolution, continental deltaic dynamics is warranted. There is importance of looking at how these landforms change at large scales, hence, the need for universal techniques. Such techniques are, unfortunately, have yet to be developed.

It is to be expected that the number of remote sensing application of delta morphology analysis will increase in the near future due to continued extensions of freely-available satellite imagery archives (e.g. Landsat, MODIS), and increased availability of higher resolution imagery via commercial and government platforms. It is therefore important to promote algorithm developments with the capability to be transferred across platforms (e.g. to efficiently upscale and downscale information from different spatial resolutions). This will enhance their longevity and utility to the entire constellation of satellites.

Direction 3: Improvement of Ancillary data

In our and others' view, inclusion of additional explanatory variables that can differentiate spectral classes is more promising than enhancement of the image processing technique alone (Khatami *et al.,* 2016). Common examples include topographic data such as digital elevation models, slope, aspect layers, geological layers, data from active sensors such as synthetic aperture radar or LiDAR, data from passive sensors, data from different temporal rates of phenological changes in vegetation mapping, and anisotropy of land surface reflectance. The inclusion of such data gives additional data layers of information that can be utilized in the problem-solving framework (e.g. Figure 7: The additional information that contributes to the understanding of deltaic evolution) to solve for the complexities of the deltaic environment more easily.

There exist challenges, however, in collecting ancillary data. Firstly, there is a regional disparity in the quantity of data collected. Although data is abundantly collected and housed in most of the economically developed countries of the world, data collection is sparse in the developing countries. Second is the bureaucracy of organizations which own these data. The lack of open data policies makes it difficult for researchers to access them. Thirdly, the culture of data sharing among researchers. Research culture should orient itself in a direction of openly sharing data subsequent to your own research for other interested parties to build up on. This culture is gathering momentum through public platforms like GitHub, researchgate, HydroShare, and stack exchanges. We however, envision the need of more subject-specific research repositories.

Direction 4: A Global Information System of deltaic data

One of the major challenges for researchers working in the domain of deltaic remote sensing is that there is a lack of ground truth data to validate their observations against. On the other hand, field geomorphologists, who base their research efforts on identifying changes in deltaic features on a local scale, would immensely benefit from the “bigger picture” of the deltaic domain from the remote sensing community. One of the major challenges has been to build a data sharing bridge between these two communities. There currently exists no portal/database/repository which offers different types of data in relation to deltaic research. A repository for river deltaic research similar to, for example, HydroShare should be established. HydroShare (Tarboton *et al.*, 2014), operated by the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI), is an online collaboration environment for sharing data, models, and code related to hydrology. A delta repository could (conceptually) include field data (e.g. soil types, point climate data, different land use types) collected by field researchers, remotely sensed data (e.g. locations and extents of deltaic features, land use class delineations, temporal change of features), different numerical models which model deltaic features (e.g. crevasse splays, avulsions, shoreline changes), and publicly volunteered and vetted geographic information. We believe that such a repository will foster collaborative and interdisciplinary research and help to propel deltaic research to the next level.

8. Conclusions

River deltas are important landforms that serve many societal and ecological functions. Assessing changes to delta morphology is important to identify vulnerable areas and sustainably manage deltaic land. Satellite remote sensing provides an effective way of detecting delta morphology change over time.

This review focused on Remote Sensing Techniques that are used in detecting delta morphology change. We discussed 18 such techniques, their strengths and their caveats with regard to deltaic feature extraction and change detection. Review of literature suggests that sub-pixel algorithms such as spectral mixture analysis and Fuzzy logic yield very high accuracies, while machine learning techniques ranked second. Support Vector Machines rank as the best individual machine learning technique across reviewed literature. We also found that the use of an ensemble of techniques (a machine learning technique ensemble, or a mix of machine learning and conventional ones) yield high accuracies.

The choice of the technique(s) that one should preferably use to extract features of a river delta is governed primarily by the complexity of the delta. Simple deltas can be analyzed using relatively simple techniques and vice versa. We also found that the choice of technique depends on how data intensive the algorithm is, the availability of resources (time and computational resource), and the skill level of the user (e.g. machine learning applications requires specific skillsets). A comparison study performed between 10 deltas using 7 algorithms yielded unsupervised classification as the go-to method for quick and robust delta-morphology-indicator detection.

We discuss the pathway forward for future research by recognizing the utility of using different delta morphology remote sensing techniques on one particular river delta to gain a better understanding of its landmass evolution, and also of the importance of comparison studies across deltas to infer on the similarities/dissimilarities of morphological changes and identify strengths limitations of remote sensing techniques themselves in different geographic/climatic conditions.

Four directions in which how future research will benefit are presented. The importance of higher spatial resolutions and the need for the development of more robust sub-pixel detection algorithms to mine data from moderate resolution imagery to more accurately infer on deltaic features such as smaller channel avulsions and formation of splays, is highlighted. The importance of automated pattern recognition techniques, universal applicability of algorithms, and algorithm-transferability across platforms are discussed. Thirdly, the effective use of ancillary data to make better judgement calls during the deltaic feature extraction process are brought forth, and finally, the concept of a repository which houses different types of data and models pertaining to deltaic research which is envisioned to foster interdisciplinary collaboration are opined.

9. References

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