Mapping and Monitoring
Mangrove Forest Baselines
Across the Globe

NATHAN MARC THOMAS

A thesis submitted in fulfilment of the requirements for the
degree of Doctor of Philosophy

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Aberystwyth University

Supervisors: Dr Peter Bunting, Dr Andrew Hardy and
Professor Richard Lucas
Declaration and Statements

Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Statement 1

This thesis is the result of my own investigations except where otherwise stated. Where correction services have been used, the extent and nature of the correction is clearly marked in footnote(s). Other sources are acknowledged by footnotes and giving explicit references. A bibliography is appended.

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Statement 2

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This work is dedicated to my family. I have always known that this could be achieved, for I have always known that you are on my side.
Abstract

Mangrove forests are woody vegetation located amongst the coastal wetlands of the tropics that hold importance for local populations, carbon sequestration and biodiversity. Despite this, mangrove forests are in decline as a consequence of both direct and indirect anthropogenic activities, such as aquaculture practices, coastal development and climate change. Through the interpretation of time-series colour composite radar imagery, mangrove forests were observed to have been anthropogenically disturbed and to have experienced changes in extent caused by natural processes. This revealed that as much as 40% of the world’s mangrove forests occur within a region at risk of further loss and degradation. In light of this observation, this study has developed a method for automatically mapping and monitoring mangrove extent using time-series Japanese (JAXA) ALOS PALSAR (2007-2010) and JERS-1 (1996) radar imagery at a variety of locations across the tropics. Random Forests was used to classify mangrove forest extent for the year 2010 at 16 study sites across the tropics, representing a broad range of mangrove habitats and forest types. Existing mangrove extent maps were refined using a Bayesian Maximum Likelihood approach and were used to generate training data for the Random Forests algorithm. Changes in mangrove forest extent were detected using a novel map-to-image approach developed in this study. The technique detected change in mangrove extent in an automated fashion for the period 2007-2010 using ALOS PALSAR imagery and 1996-2010 using JERS-1 imagery. An area in excess of 2.5 million ha of mangrove forest extent was classified with the baseline and changes in extent mapped with an accuracy >90%. Limitations pertaining to image registration, classification error and the size of the minimum mapping unit were identified as sources of error in the baseline and change detection mapping. The results of this work are applicable at the global level and can be scaled to update the existing map of global mangrove forest extent and implement a mangrove monitoring system.
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<td>A.81</td>
<td>Mangrove gain at Kakadu National Park, Australia</td>
<td>356</td>
</tr>
<tr>
<td>A.82</td>
<td>Mangrove loss at Kakadu National Park, Australia</td>
<td>357</td>
</tr>
</tbody>
</table>
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Chapter 1

Introduction

This chapter provides a descriptive overview of mangrove forests, including the ecosystem services that they provide and the causes of the decline in their extent. This is followed by a brief overview of how this work will serve policy and decision makers through the implementation of an operational monitoring system. The chapter concludes by providing the aim of the work and an outline of the thesis structure.

1.1 Mangrove species

Mangroves are defined as woody trees and shrubs that inhabit tropical coastal regions and are commonly referred to as a mangrove forest or mangal (Hogarth, 1999). Hogarth (1999) defines 54 species in 30 genera, belonging to 16 families whilst (Chapman, 1976) estimates that there are approximately 70 species of mangrove worldwide, in agreement with Alongi (2002). The majority of mangroves are composed of shrubs and trees of varying height with additional lianes, fern and palm species. Mangrove height varies with species and ranges from small shrubs below 1 m in height to over 30 m. The most abundant families of mangroves are Rhizophoraceae, Avicenniaceae, Combretaceae, Plumbaginaceae and Sonneraticeae (Chapman, 1976).
A number of species are constituent species which are commonly and repeatedly found in mangals. These species are termed the major elements of the mangal and are defined by Tomlinson (1986) as having complete fidelity to the mangrove forest and a range of specific characteristics. These include an ability to dominate the structure of the stand, being specialized to their environment, possessing a mechanism of salt exclusion/tolerance and having sufficient taxonomic independence and diversity from terrestrial counterparts. The major elements of the mangrove environment are summarised in Table 1.1.

Table 1.1: Major elements of a mangrove forest (mangal). Taken from Tomlinson (1986).

<table>
<thead>
<tr>
<th>Family</th>
<th>Genus</th>
<th>No. of species</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avicenniaceae</td>
<td>Avicennia</td>
<td>8</td>
</tr>
<tr>
<td>Combretaceae</td>
<td>Lagularia</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Lumnitzera</td>
<td>2</td>
</tr>
<tr>
<td>Palmae</td>
<td>Nypa</td>
<td>1</td>
</tr>
<tr>
<td>Rhizophoraceae</td>
<td>Bruguiera</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Ceriops</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Kandelia</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Rhizophora</td>
<td>8</td>
</tr>
<tr>
<td>Sonneratiaceae</td>
<td>Sonneratia</td>
<td>5</td>
</tr>
</tbody>
</table>

These major species are accompanied by a series of minor species. These species are unable to dominate mangrove forests and may only form small stands, forced to form peripheral habitats within the mangal.

1.2 Biogeographical distribution

Mangrove forests are tropical in their extent and occupy the coasts of both the northern and southern hemispheres. Their northern extent reaches latitudes ranging in 24°–32°N which correlates with ocean temperature and is commonly curtailed by the winter position of the 20°C isotherm. In the southern hemisphere mangroves extend further south along the eastern margins of land masses than on the western margins but can reach extents of 38°45’S. Species diversity is correlated with latitude with the number of species observed to decrease as the maximum extents of mangrove range are approached (Tomlinson, 1986).
Mangroves occur in two longitudinally distinct regions known as the Indo-West Pacific (IWP) region and the Atlantic-Caribbean-East Pacific (ACEP) region. The IWP region is composed of the eastern coast of Africa, including the red sea, the breadth of the Indian ocean to Australia and New Zealand and north to the Philippines and southern Japan, reaching an eastern extent at Samoa. The ACEP region includes the western coast of Africa and the eastern and western coasts of central and southern America. These regions can be further divided into smaller regions with the IWP region containing 3 sub-regions, composed of east Africa and the middle-east, southern Asia and Southeast Asia and thirdly, Australasia and New Zealand. The ACEP region is subdivided into the west coast of Africa and the east and west coast of central and south America. These six sub-regions largely exhibit the same major species of mangrove within the enveloping ACEP and IWP region, although substantial species diversity is observed between the ACEP and IWP regions. The species diversity in the IWP region is almost four times greater than that in the ACEP region, with a total of 58 taxa to a total of 13, respectively. The genera within these families is limited in diversity with 23 in the ACEP and only eight in the IWP, sharing only three genera across the two ecoregions. The global distribution of mangroves is provided in Figure 1.1.
Figure 1.1: World distribution of mangroves. Reproduced from the first global mangrove map derived from remotely sensed data (Landsat) (Giri et al., 2011). Inserts present mangrove forest extent at a variety of locations across the tropics.
1.3  Zonation and succession

Mangroves typically exhibit a range of vegetation ‘zones’, whereby a profile across a mangal would reveal a progression from the coast, inland through a series of pure mono-dominant stands. This species zonation follows a sequence of species from the coast to the climax vegetation, with regular reoccurring intervals of a species or the gradation of species across whole deltas. A diagram of a proposed vertical sequence of species is presented in Figure 1.2. This diagram presents plant succession where pioneer species establish at the coast and mature inland until stable climax species are established. This diagram, however, is simplified as the causes of zonation varies spatially and temporally (Hogarth 1999). Mangals may appear to exhibit no zonation at all, forming clusters of mangroves, resulting in diverse stands which are shaped by the characteristics of the surrounding environment. In these instances the zonation is present but becomes less discernible. Physical gradients are one of the key controls on the zonation of mangroves. These gradients define the zonation of vegetation as different species have varying tolerances to inundation, salinity and sediment loads (Hogarth 1999).

Figure 1.2: Mangrove shore profile in north-eastern Australia. HWS is the highest level of spring tide high water. (Redrawn from Tomlinson 1986).
1.4 Biophysical attributes

Mangrove forests are unique in their ability not only to survive but actively thrive in saline aquatic environments, exhibiting unique characteristics and coping abilities in comparison to their terrestrial forest counterparts. This ability separates mangrove forests as the only woody, high biomass vegetation capable of this. These mechanisms, as outlined by Hogarth (1999) include:

**Inundation**  Mangrove soils are either regularly or permanently waterlogged, limiting the availability of oxygen for respiration by the underground tissue. Oxygen that is present in waterlogged soil is depleted by aerobic respiration of soil bacteria, forming almost completely anoxic soil. To attain the required oxygen for respiration, mangrove species have developed roots that breach the surface of the soil, in order to maximise gaseous exchange. Examples of the root networks of a variety of mangrove species are presented in Figure 1.3. These roots are in addition to the typical ‘stilt’ roots that provide support for the tree in the soft underlying substrate and which are capable of diverging from the tree by as much as 2 m above ground. The exposed roots and pneumatophores are then able to transfer oxygen to the cells in the submerged portion of the root.

**Halotolerance**  Mangroves thrive in marine environments and are regularly inundated by tides. In highly saline water the osmotic potential is negative, forcing mangrove roots to have to overcome this negative pressure. Mangroves utilise one of three methods of coping with high salinity, using either exclusion to salt, secretion of salt or tolerance of salt. Species of *Aegiceras* and *Avicennia* exclude as much as 97% of salt through the roots with xylem sap having a salt concentration akin to approximately 10% of the concentration in sea water (Tomlinson, 1986). Other mangrove species deposit salt on the bark, along stems, and along roots, whilst others are capable of depositing salt in leaves which are then shed. Other species secrete salt on to the surface of leaves and use hairs to elevate the secreted salt water above the leaf surface to avoid osmotic withdrawal of water.
1.5 Mangrove productivity and carbon

Mangroves are capable of growing to heights above 30 m and are subsequently able to attain high values of above ground biomass (AGB). These were observed in Malaysia, in a *R. apiculata* dominated mangle forest (Putz and Chan, 1986) to reach a maximum of 460 Mg ha\(^{-1}\). Other high estimates of aboveground biomass (> 300 Mg ha\(^{-1}\)) have been estimated at both Indonesia (Komiyama et al., 1988) and French Guiana (Fromard et al., 1998). The above ground biomass of mangrove forests has been observed to decrease with increasing latitude and decreasing stand age to estimates of approximately 100 Mg ha\(^{-1}\). Despite this, forests dominated by *Avicennia* has been estimated to contain as much as 341 Mg ha\(^{-1}\).
Table 1.2: Species variation with mechanisms of coping with salt (Hogarth, 1999).

<table>
<thead>
<tr>
<th>Species</th>
<th>Exclude</th>
<th>Secrete</th>
<th>Accumulate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acanthus</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aegialitis</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Aegiceras</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Avicennia</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Bruguiera</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ceriops</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excoecaria</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laguncularia</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Obsornia</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Rhizophora</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Sonneratia</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Xylocarpus</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

as far south as 27°S (Mackey, 1993). A range of AGB value for mangroves distributed across the tropics is given Table 1.3.

Often overlooked, but a prominent portion of the total mangrove forest biomass, is the below-ground biomass. Estimates suggest that below-ground biomass can account for substantial quantities of the total mangrove forest biomass, with as much as 171 Mg ha\(^{-1}\) present at the equator up to 30° latitude. This is less than the equivalent above ground biomass available (283.6 Mg ha\(^{-1}\)), but nevertheless ascertains to the quantity of below-ground biomass within mangrove forests (Twilley et al., 1992). Estimates of below ground biomass within a *Rhizophora* spp. dominated forest reached 272.9 Mg ha\(^{-1}\) (Komiyama et al., 1987) whilst values of 196.1 Mg ha\(^{-1}\), 180.7 Mg ha\(^{-1}\) and 177.2 Mg ha\(^{-1}\) have been reported from *Rhizophora* dominated forests (Komiyama et al., 1988).

These high values for biomass provide the soil with a large quantity of organic carbon inputs. These organic inputs add to the carbon flux of mangrove environments and contribute to them being one of the largest natural carbon stores in the tropics.
Table 1.3: The variation in mangrove species, region and stand age with above ground biomass (AGB). Extract from Komiyama et al. (2008).

<table>
<thead>
<tr>
<th>Location</th>
<th>Species</th>
<th>Age/condition</th>
<th>AGB Mg ha(^{-1})</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malaysia</td>
<td><em>R. apiculata</em></td>
<td>&gt;80</td>
<td>460.0</td>
<td>Putz and Chan (1986)</td>
</tr>
<tr>
<td>Australia</td>
<td><em>A. marina</em></td>
<td>Secondary forest</td>
<td>341.0</td>
<td>Mackey (1993)</td>
</tr>
<tr>
<td>Indonesia</td>
<td><em>R. apiculata</em></td>
<td>Primary forest</td>
<td>299.1</td>
<td>Komiyama et al. (1988)</td>
</tr>
<tr>
<td>Thailand</td>
<td><em>Rhizophora spp.</em></td>
<td>Primary forest</td>
<td>281.2</td>
<td>Tamai et al. (1986)</td>
</tr>
<tr>
<td>India</td>
<td><em>Rhizophora</em></td>
<td>Primary forest</td>
<td>214.0</td>
<td>Mall et al. (1991)</td>
</tr>
<tr>
<td>Australia</td>
<td><em>A. marina</em></td>
<td>Primary forest</td>
<td>144.5</td>
<td>Briggs (1977)</td>
</tr>
<tr>
<td>Japan</td>
<td><em>B. gymnorrhiza</em></td>
<td>Primary forest</td>
<td>97.6</td>
<td>Suzuki and Tagawa (1983)</td>
</tr>
<tr>
<td>Sri Lanka</td>
<td>Mixed forest</td>
<td>Riverine</td>
<td>85.0</td>
<td>Amarasinghe and Balasubramaniam (1992)</td>
</tr>
<tr>
<td>Indonesia</td>
<td><em>B. parviflora</em></td>
<td>Concession area</td>
<td>42.9</td>
<td>Kusuma et al. (1992)</td>
</tr>
<tr>
<td>French Guiana</td>
<td><em>Laguncularia, Avicennia, Rhizophora</em></td>
<td>Matured Coastal</td>
<td>315.0</td>
<td>Fromard et al. (1998)</td>
</tr>
<tr>
<td>Kenya</td>
<td><em>R. mucronata</em></td>
<td>Primary forest</td>
<td>249.0</td>
<td>Slim et al. (1996)</td>
</tr>
<tr>
<td>French Guiana</td>
<td><em>Rhizophora, Avicennia</em></td>
<td>Senescent forest</td>
<td>143.3</td>
<td>Fromard et al. (1998)</td>
</tr>
<tr>
<td>Kenya</td>
<td><em>C. tagal</em></td>
<td>Primary forest</td>
<td>40.1</td>
<td>Slim et al. (1996)</td>
</tr>
<tr>
<td>Florida</td>
<td><em>R. mangle</em></td>
<td>Not Available</td>
<td>7.9</td>
<td>Lugo and Snedaker (1974)</td>
</tr>
</tbody>
</table>
As a consequence of the large biomass values in mangrove environments, mangrove ecosystems are capable of storing large quantities of carbon. The rate of material burial and carbon storage is generally low with as little as 10-17% of primary production becoming buried in the sedimentary pool, with the remainder being decomposed, exported, consumed or unaccounted for (Duarte and Cebrián, 1996). The efficiency of carbon burial has been observed to increase with forest age, with mature mangrove forests (85 years) capable of sequestering more than one and a half times as much carbon (27%) than young forests (5 years, 16%) (Alongi et al., 2004). Studies of soil respiration and subsequent release of CO$_2$ have been limited, but CO$_2$ flux has been measured in mangrove forests in Australia and southern Thailand. The forests were observed to be net autotrophic with a net production of 5.56 Mg C ha$^{-1}$ yr$^{-1}$ (Alongi et al., 2000, 2001). This was supported by a study of mangrove forests where the average Net Ecosystem Production (NEP) was below 4.5 Mg C ha$^{-1}$ yr$^{-1}$ in stands ranging from 30 to 120 years old (Pregitzer and Euskirchen, 2004). Total Organic Carbon (TOC) concentrations in mangrove soils have been measured to befall within the range of 0.08% to 21.8% (mean 0.78%) (Tue et al., 2012) and have been estimated to be amongst the most carbon rich ecosystems in the tropics. Mangrove soils store an average of 1,023 Mg C ha$^{-1}$ and range in depth from 0.5 to 3 m. These soils store 49–98% of the total carbon in these ecosystems, highlighting the dominance of the carbon in the soil over the AGB. The total release of carbon into the atmosphere is estimated to be 0.02–0.12 Pg per year, a value equitable to 10% of total emission of carbon from deforestation, despite accounting for <1% of tropical forest area (Donato et al., 2011). The large carbon content of mangrove ecosystems in comparison to other terrestrial forest ecosystems is shown in Figure 1.4.
1.6 Mangrove uses

Figure 1.4: Comparison of mangrove C storage (mean 95% confidence interval) with that of major global forest domains (Donato et al., 2011).

1.6.1 Direct products

The primary practical uses of mangrove products include timber for construction of buildings, furniture and boats. Medium scale trades and industries are dependent on timber for fuel to produce bricks and lime, baking, brewing and in textile manufacture. The bark and leaves are used for a plethora of medicinal purposes. Whilst these uses of mangrove forests appear to be of subsistence use, they also hold an economic value for coastal communities with timber derived from species
CHAPTER 1. INTRODUCTION

of *Rhizophora* spp. and *A. germinans* holding a commercial value (Field, 1995; Bandaranayake, 1998; Nfotabong-Atheull et al., 2011). Beyond the use of mangrove products for economic gain and necessary practical use, mangrove products also have important traditional uses that are intrinsic to local indigenous cultures. A large number of examples of use of mangrove forest products are provided in Table 1.4.

Table 1.4: Examples of uses of mangrove forests to local populations.

<table>
<thead>
<tr>
<th>Use/Service</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fishing</td>
<td>Walton et al. (2006)</td>
</tr>
<tr>
<td>Fish nursery</td>
<td></td>
</tr>
<tr>
<td>Increases biodiversity</td>
<td></td>
</tr>
<tr>
<td>Sediment trapping</td>
<td></td>
</tr>
<tr>
<td>Fuel</td>
<td>Hussain and Badola (2010)</td>
</tr>
<tr>
<td>Timber</td>
<td></td>
</tr>
<tr>
<td>Water filtering</td>
<td></td>
</tr>
<tr>
<td>Animal fodder</td>
<td></td>
</tr>
<tr>
<td>Aesthetic environments</td>
<td></td>
</tr>
<tr>
<td>Shoreline protection</td>
<td>Mazda et al. (2006)</td>
</tr>
<tr>
<td>Antibacterial properties</td>
<td>Abeysinghe (2010)</td>
</tr>
<tr>
<td>Extraction of alkaloids, steroids</td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>Dahdouh-Guebas and Mathenge (2000)</td>
</tr>
<tr>
<td>Fuel</td>
<td></td>
</tr>
<tr>
<td>Charcoal</td>
<td></td>
</tr>
<tr>
<td>Boat building</td>
<td></td>
</tr>
<tr>
<td>Medicines</td>
<td>Kovacs (1999)</td>
</tr>
<tr>
<td>Dyes/tans</td>
<td></td>
</tr>
<tr>
<td>Furniture making</td>
<td></td>
</tr>
<tr>
<td>Tobacco galleries</td>
<td></td>
</tr>
<tr>
<td>Stakes &amp; poles</td>
<td></td>
</tr>
<tr>
<td>Fish traps</td>
<td></td>
</tr>
<tr>
<td>Fences/walls</td>
<td></td>
</tr>
<tr>
<td>Textile manufacturing</td>
<td>Bandaranayake (1998)</td>
</tr>
<tr>
<td>Fibres/ropes</td>
<td></td>
</tr>
<tr>
<td>Perfumes</td>
<td></td>
</tr>
<tr>
<td>Food</td>
<td></td>
</tr>
<tr>
<td>Insecticides</td>
<td></td>
</tr>
<tr>
<td>Cooking oil</td>
<td></td>
</tr>
</tbody>
</table>

The traditional medicinal uses of mangroves have been outlined but a variety of alkaloids and saponins are readily derived from mangroves that have an interest to modern industry and in the manufacture of modern medicine (Bandaranayake, 1998), including antioxidant, antibacterial and antiherpetic properties (Patra and Thatoi, 2011).
1.6. MANGROVE USES

1.6.2 Indirect products and services

Indirect products and services provided by the mangrove are equally as important as the direct products. Such products, which include economic gain and ecosystem services, are able to support communities over a longer timescale than the short-term benefits derived from direct uses of mangrove products. The number and type of indirect products from mangrove forests is large and varied, with different mangrove environments offering different products. The range of goods and services include sediment trapping, the production of nutrients and organic matter through detritus and shoreline protection Ewel et al. (1998). These products are derived differently from different mangrove settings and vary spatially.

Mangrove forests also have the capacity to provide economic benefits to those who live and work within them. The mangroves of the Bhitarkanika Conservation Area, east coast of India, provide as much as 30% of income for households that reside within the immediate vicinity of the mangrove forest (Hussain and Badola, 2010). This is supported by Rönbäck (1999), in a study that highlights the undervaluation of the natural products and ecological services generated by mangrove ecosystems such as capture fisheries which can reach a value as high as US$ 16,750 ha\(^{-1}\).

The capacity of mangrove forests to protect coastal regions has been debated. The role mangroves play in the accretion of sediment along coastal margins has been documented, but investigations into the protective properties of mangrove forests against tsunamis have been less conclusive. The effectiveness of mangrove forests against high-energy events is a function of a plethora of environmental settings that include the size and characteristics of the forest and the size and speed of the event (Alongi, 2008). The protective capacity of mangroves along the Andaman coast of Thailand was demonstrated after the December 2004 Indian Ocean tsunami with villages along the coast suffering significantly more damage than those that were situated behind a buffer of mangroves. It is acknowledged, however, that the findings were not investigated as to whether they could effectively and accurately be generalised (Chang et al., 2006). Models of
the wave attenuating properties of mangrove forests support this (Massel et al., 2009; Mazda et al., 2006, 1997), but are unable to fully represent a real world event, which may include unaccounted parameters or abnormal wave heights and energy (Yanagisawa et al., 2009).

1.7 Biodiversity in mangrove forests

Mangrove forests, as with other tropical forest land cover types, support a wide variety of fauna and provide crucial support for biodiversity within wider coastal ecosystems. Mangrove forests, however, are distinguished from other tropical land cover types by occupying the riparian zone, straddling both the terrestrial and marine environments. In doing so, mangroves demonstrate a steep environmental gradient from one ecoregion to another. This enables them to host a wider variety of fauna than their terrestrial and marine counterparts (Hogarth, 1999; Luther and Greenberg, 2009).

1.7.1 Benthic zone

Supporting biodiversity of the marine ecosystem is a role almost unique to mangrove forests, in comparison to other tropical terrestrial vegetation. The benthic zone is the first zone of biodiversity that a mangrove forest can support and is the ecological zone associated with the lowest level of a body of water, including the surface sediment and limited sub-surface layers. In mangrove forests, the benthic zone supports meiobenthos species (Alongi, 1987b) and larger nematode communities (Alongi, 1987a) alongside high macrofaunal and meiofaunal densities (Alongi and Christoffersen, 1992).

As mangroves provide a habitat for a range of epibionts, beyond those mentioned to include macroalgae, hydrozoans, ascidians, sponges, anemones, hard corals and isopod crustaceans, they are simultaneously influenced by the species they support. Root-fouling epibionts and root herbivores are direct determinants in the growth and production of mangroves, emphasising that mangroves and the ecosystems they support engage in complex interactions and feedback mechanisms and that one can thrive at the expense of the other (Ellison and Farnsworth, 1992).
1.7. BIODIVERSITY IN MANGROVE FORESTS

A full list of the benthic species a mangrove can support is provided in Table 1.5.

Table 1.5: The range of benthic organisms that rely upon mangrove ecosystems.

<table>
<thead>
<tr>
<th>Benthic Species</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed meiobenthic species</td>
<td>Alongi (1987a)</td>
</tr>
<tr>
<td>Nematodes</td>
<td>Alongi (1990)</td>
</tr>
<tr>
<td>Phytobenthic species</td>
<td>Ansari et al. (1993)</td>
</tr>
<tr>
<td>Turbellarians (flatworms)</td>
<td></td>
</tr>
<tr>
<td>Mixed harpacticoids</td>
<td>Lee (2008)</td>
</tr>
<tr>
<td>gastropods</td>
<td></td>
</tr>
<tr>
<td>Oligochaetes</td>
<td>Ellison and Farnsworth (1992)</td>
</tr>
<tr>
<td>Macroalgae</td>
<td></td>
</tr>
<tr>
<td>Hydrozoans</td>
<td></td>
</tr>
<tr>
<td>Ascidians</td>
<td></td>
</tr>
<tr>
<td>Sponges</td>
<td></td>
</tr>
<tr>
<td>Anemones</td>
<td></td>
</tr>
<tr>
<td>Corals</td>
<td></td>
</tr>
<tr>
<td>Isopods</td>
<td></td>
</tr>
<tr>
<td>Shrimp</td>
<td>Crona and Rönnbäck (2005)</td>
</tr>
</tbody>
</table>

1.7.2 Pelagic zone

Above the benthic zone is the pelagic zone, which is the water column from the benthic zone to the water surface. This is a habitat for a high number of species of fish (Blaber and Milton, 1990) as a consequence of the unique environment that mangroves create. The prop-roots of the mangroves provide a unique habitat for fish assemblages and have been observed to contain the highest relative mean density and diversity of fish in the mangrove environment (Eggleston et al., 2004). A larger number of large gamefish and more importantly, a greater number of rare and threatened fish species, have been observed to dwell within mangrove habitats than any other adjacent habitats (Eggleston et al., 2004).

The attraction of mangrove forests to fish species as a consequence of high food abundance is well understood and accepted, yet mangroves offer other properties which are unique to them over adjacent habitats. Two such properties are habitat complexity and shade. These refer to the shelter provided by the habitat, with mangrove roots providing abundant cavities and shade, which offer a form of shelter from predators (Cocheret De La Morinière et al., 2004).
A somewhat debated function of mangrove forests is their role as nurseries for juvenile fish. Nurseries, in this sense, can be described as a habitat that is supportive of juvenile fish species as they make the ontogenetic transformation into an adult (Adams et al. 2006). This role of mangroves is supported by Robertson and Duke (1987) and Dorenbosch et al. (2005) in their observations that mangroves support a greater number of post-larval juvenile and small adult fish than other adjacent habitat types. However this is contested as being species specific and are suggested as being no more valuable than the nursery function offered from other adjacent habitats (Dorenbosch et al. 2004, 2005; Cocheret de la Morinière et al. 2002).

The pelagic zone also supports organisms which, like mangroves themselves, straddle the aquatic and terrestrial environments. Amphibious species are rare in mangrove forests due to the saline environment, although a limited species of frog and toad use mangroves as a habitat (Hogarth 1999). Reptilian species are more akin than amphibious species to inhabiting salt water and brackish environments and as a result are more abundant in mangrove environments with crocodiles observed within the mangroves of Northern Australia and Sri Lanka (Santiapillai and de Silva 2001). Similarly species of turtle and a plethora of sea-snakes are abundant in both the IWP and ACEP ecozones (Rasmussen et al. 2011). A full list of the pelagic species is provided in Table 1.6.

Table 1.6: The range of pelagic organisms that rely upon mangrove ecosystems.

<table>
<thead>
<tr>
<th>Pelagic Species</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed Fish species</td>
<td>Blaber and Milton (1990); Eggleston et al. (2004)</td>
</tr>
<tr>
<td>Crabs</td>
<td>Frusher et al. (1994)</td>
</tr>
<tr>
<td>Gastropods</td>
<td>Ashton et al. (2003)</td>
</tr>
<tr>
<td>Molluscs</td>
<td>Cantera et al. (1983); Ashton et al. (2003)</td>
</tr>
<tr>
<td>Frog/Toad</td>
<td>Hogarth (1999)</td>
</tr>
<tr>
<td>Crocodiles</td>
<td>Santiapillai and de Silva (2001); Platt and Thorbjarnarson (2000a)</td>
</tr>
<tr>
<td>Turtle</td>
<td>Platt and Thorbjarnarson (2000b); Webb et al. (1977)</td>
</tr>
<tr>
<td>Snakes</td>
<td>Rasmussen et al. (2011)</td>
</tr>
</tbody>
</table>
1.7.3 Terrestrial zone

The biodiversity of the terrestrial ecoregion is dominated by mammals, birds and insects. Mammals such as otters are common amongst brackish waters with accompanying mangrove shores, attracted by the abundant food sources that the mangroves support (i.e. crabs) [Angelici et al., 2005]. Also at the ground level, large mammals are able to utilise mangrove forests for grazing or for hunting other animals that inhabit the forest. Much of the wide range of biodiversity that mangroves support are predated upon by other species. As the number of species are in such abundance, mangroves become prime locations for predators to hunt, providing a food source to support niche species such as the Royal Bengal tiger [Gopal and Chauhan, 2006]. Above the ground, monkeys can make a habitat of the mangrove canopy, spending as much as 85% of their time within the mangrove forest [Nowak, 2008; Gippoliti and Dell’Omo, 1996].

The canopy supports species which are able to utilise the full vertical extent of the mangrove and is subsequently a primary habitat for birds and bats [McCracken et al., 1997; Wiles et al., 1997; Bordignon, 2006]. Similarly, the canopy supports a wide range of bird species and is able to support locally threatened species and provide a habitat where they can breed [Lefebvre and Poulin, 1997; Sodhi et al., 1997]. A full list of the terrestrial species is provided in Table 1.7.

Table 1.7: The range of terrestrial organisms that rely upon mangrove ecosystems.

<table>
<thead>
<tr>
<th>Terrestrial Species</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Otter</td>
<td>Angelici et al. (2005)</td>
</tr>
<tr>
<td>Buffalo</td>
<td>Dahdouh-Guebas et al. (2005)</td>
</tr>
<tr>
<td>Bengal tiger</td>
<td>Gopal and Chauhan (2006)</td>
</tr>
<tr>
<td>Primates/monkey</td>
<td>Nowak (2008); Gippoliti and Dell’Omo (1996)</td>
</tr>
<tr>
<td>Bats</td>
<td>McCracken et al. (1997); Wiles et al. (1997); Bordignon (2006)</td>
</tr>
<tr>
<td>Birds</td>
<td>Lefebvre and Poulin (1997); Sodhi et al. (1997)</td>
</tr>
</tbody>
</table>

The foundation of the trophic levels for the vast majority of the biodiversity contained within the mangrove forest is the abundance of insects. Nagelkerken et al. (2008) review in detail the insects that are commonly found in mangroves.
and divide them into 3 categories. These make up the primary trophic groups and they include herbivorous insects that feed on live plant material, saproxylic and saprophagous insects that feed on dead plant material and litter and parasitic and predatory insects that feed on other insects or animals. A full review of insects and other terrestrial and marine fauna within mangrove forests is provided by Nagelkerken et al. (2008).

1.8 Mangrove degradation: losses and causes

Despite their importance for carbon sequestration, biodiversity and supporting indigenous local communities, mangrove forests are greatly threatened across their entire range. The latest estimate of mangrove extent by the FAO, estimated that in 2005 the total areal extent of mangroves was 15.2 million ha. This estimate is much lower than the previous FAO estimate in 1980 of 18.8 million hectares (FAO, 2007). Over the period between the two estimates, mangroves may have lost 4 million hectares in areal extent at an approximate rate of loss of 0.16 million ha yr\(^{-1}\). The rate of mangrove degradation throughout the 1990s was estimated at 1% \(\text{yr}^{-1}\); a rate twice that of rainforests over the same period (Mayaux et al., 2005). Comparatively, 30% of total tropical terrestrial forest has been lost as a consequence of anthropogenic activity since monitoring began, whilst it is estimated that one third of total mangrove forest has been lost over the last half-century alone (Alongi, 2002). The loss of mangroves across the globe is deemed so critical that from the 70 true species of mangrove, as many as 11 have been evaluated to meet the criteria of the three Red List categories of threat (Polidoro et al., 2010).

The primary cause of this degradation is from aquaculture practices. Aquaculture is expected to grow with population and will unlikely subside until the rate of human population growth begins to abate. Aquaculture is expected to account for the expected depletion of natural mangrove stocks and will push mangroves beyond their level of sustainable use. Furthermore, the expansion of the coastal zone that will accompany a predicted increase in human population rise will con-
tribute more effluent and hydrocarbon run-off into mangrove forests, compounded by the growing need for land along the coastal zone (Alongi, 2002). The causes of mangrove degradation can be grouped into three categories. These include anthropogenic forcing, natural influences and climatically induced change. The most influential of these are anthropogenic and climatically induced changes.

1.8.1 Anthropogenic forcing

1.8.1.1 Aquaculture

In an assessment of mangrove forest extent and loss at a variety of locations in the Americas, Africa, Asia and Australia, the greatest cause of mangrove loss was evaluated to be due to mariculture practices. A total loss from all causes of $36 \times 10^3$ km$^2$ was estimated from countries containing 66% of the total area of mangrove forest. Of the loss of mangroves derived from the consolidated data, shrimp culture was responsible for as much as 52% (Valiela et al., 2001). Aquaculture is the fastest growing animal-food sector in the world. In 2011, fish from aquaculture practices accounted for nearly half of the total fish consumed worldwide (45.6%). The production of fish from aquaculture grew substantially throughout the 2000s and increased to a total of 52.5 million tonnes in 2008 from 32.4 million tonnes in 2000. Developing countries have remained the vast source of this production, with the Asia-Pacific region accounting for almost 90% of global production. Over half of the total global consumption of fish was forecast to be derived from aquaculture by 2012 (FAO, 2011), exposing mangrove environments to increased pressures from anthropogenic activity.

Aquaculture has a plethora of direct and indirect detrimental impacts upon a mangrove forest. These include the immediate loss of mangroves for pond construction (Figure 1.5), alongside a suite of indirect impacts. These include, but are not limited to, the alteration of natural tidal flows, release of toxic wastes, reduced water quality and alterations to sedimentation rates and turbidity (Alongi, 2002). Impacts such as these have been witnessed in locations such as the Gulf of California ecoregion which experienced changes in the hydrological pattern, hyper-
salinity, eutrophication, disease and deterioration of the water quality following the conversion of the region to aquaculture (Páez-Osuna et al., 2003).

![Image](image1.png)

Figure 1.5: Destruction of mangrove forests for aquaculture. Photograph in Valiela et al. (2001) by Fans Lanting, Miden Pictures.

The impacts of aquaculture are able to persist in the environment and continue to degrade mangrove forests once the aquaculture exceeds its lifespan of 5–10 years (Flaherty and Karnjanakesorn [1995]). The acidification of the soil can prevent mangroves from recolonising a decade after the shrimp pond is abandoned. As aquaculture ponds are excessively nutrient rich in comparison with the surrounding water, the leaching of the aquaculture into the freshwater system causes eutrophication and subsequent loss of oxygen in the water (Wolanski et al., 2000; Trott and Alongi, 2000).

The practice of aquaculture and subsequent damage to mangrove forests is tolerated due to a range of institutional issues. One of these has been mangroves being viewed as wasteland and not valued for the range of ecosystem services that they provide. This has promoted the conversion of these wetlands to shrimp farms, viewed as a better use of the mangrove forest. The degradation of the mangrove is further compounded by i) the low economic value of the mangroves so that the land is readily and cheaply acquired, ii) conflicting policies that overlap and cause unnecessary bureaucracy and iii) corruption leading to the low enforce-
1.8. MANGROVE DEGRADATION: LOSSES AND CAUSES

 ment of any protective legislation. These institutional issues are enveloped by an overriding lack of political will to ensure that the mangrove area is protected (Primavera, 2000).

1.8.1.2 Coastal development

Coastal development, driven by increasing tourism, is applying evermore pressure upon the coastal zone. Along the West coast of India alone, approximately 40% of the mangrove has been lost as a direct consequence of agriculture and urban development within the coastal zone (Upadhyay et al., 2002). The construction of a road and water treatment works between 1997 and 2000 at Punta Mala Bay, Panama, caused 100% loss of mangroves in some areas as a direct consequence of the coastal development (Benfield et al., 2005). This was mirrored on the Bragantinian mangrove peninsula, North Brazil, where mangroves were cleared for the construction of houses as a consequence of the pressures of increasing tourism (Krause and Soares, 2004). The arrival of coastal development into a region brings with it a suite of environmental problems. This is exacerbated if the development is industrial and waste products are purposely or inadvertently released into the surrounding environment (Yim and Tam, 1999). Similarly, oil spills from a tanker ship and a land tanker killed as much of 6% of the Bahia Las Minas mangroves in Panama (Duke et al., 1997) whilst herbicides were deduced as being responsible for the widespread dieback, degraded canopy condition and deterioration in seedling health of mangroves in the Mackay region of NE Australia, affecting over 30 km$^2$ in little over a decade (Duke et al., 2005).

1.8.1.3 Population increase

The pressures forced upon the coastal zone are unlikely to abate, with an anticipated population increase upon the coastal zones of the world in the coming century, (Figure 1.6). The global population of 7.2 billion (mid-2013) is expected to increase to 8.2 billion in little over the next decade, reaching 8.1 billion by 2025, 9.6 billion by 2050 and 10.9 billion by 2100. Of the 3.7 billion increase by 2100, almost all will occur in developing countries. In these countries, population will likely concentrate along the coastal zone. The vast proportion (72%) of the
63 most populated urban areas across the globe with populations over 5 million in 2011 were located on or near the coastal zone (FAO 2013, 2012).

1.8.2 Natural influences

The pressures applied on mangrove forests, however, are not all anthropogenic. Natural factors are also capable of degrading mangrove environments. Natural phenomena that have the capacity to affect a large area of mangroves over a short time are large sudden high water events and extreme metrological conditions. Damage to mangroves from hurricanes has been well documented, ranging from extensive windthrow and defoliation of forests in Darwin, Australia, the uprooting and trunk-snapping of as much as 95% of mangroves in Everglades National Park, damage to 4700 ha of mangroves in the Dominican Republic, and the mass mortality of trees and subsequent peat collapse in Honduras (Woodroffe and Grime 1999; Smith III et al. 1994; Sherman et al. 2001; Cahoon et al. 2003). Extreme precipitation events such as monsoons are expected to increase in frequency in the coming century with increased precipitation and storm period (Stocker et al. 2014). The location of mangroves along the coastal zone also positions them in the direct path of incoming tsunamis.

1.8.3 Climate change

As we move increasingly through an era of unprecedented climate change, Earth’s climate will undergo changes that are currently not known with certainty. One of the greatest threats to mangrove forests from climate change will be of rising sea levels. Mean global sea level has risen by almost 20 cm from the beginning of the 20th Century. Sea level rise is expected to continue and accelerate over the coming century, with an increase in mean sea level by as much as 1 m by 2100 (Figure 1.7). Although sea level rise will not be uniform throughout the oceans, 70% of the world’s coastlines are estimated to experience sea level rise falling within 20% of the global mean (Stocker et al. 2014).
Figure 1.6: Estimated population increase by 2060, particularly in the developing nations of Southeast Asia, will exert more pressure upon the mangroves in the region (Figure Neumann et al. (2015)).
Sea level rise can present both a threat and an opportunity for mangrove forests. Mangroves are known to accrete sediment (Cheong et al., 2013), from trapping sediment suspended when inundated or through the build-up of peat through the decomposition of organic matter. The survival of mangrove forests in the face of sea level rise is therefore dependent on whether sediment is accreted at the same rate as sea level rise (McKee et al., 2002; Hashimoto et al., 2006). This, however, is too simplistic as morphological changes that occur over large areas, such as tectonic uplift, can change the sea level of an entire region so that sea level rise will not affect all mangroves to the same rate (Hogarth, 1999).

Should sea levels rise above the rate of the terrestrial surface, through subsurface movement or sediment accretion, mangroves will either face periods of longer inundation or will migrate landwards into new areas (Lu et al., 2013). The mangrove area of the Ten Thousand Islands region of Florida, experienced a 35% increase in mangrove area over 78 years as consequence of sea level rise (Krauss et al., 2011). Mangroves, however, are sensitive to salinity and have been observed to inhibit mangrove growth at increasing concentrations (Ye et al., 2010). Mangroves that are unable to adapt to increased frequency and periods of inundation will migrate landwards into traditionally fresh and brackish water environments that are also modified by encroaching salinity as a consequence of sea level rise. This may cause changes in species composition within mangrove forests as R. mangle is capable of coping with extended periods of inundation whilst L. racemosa and A. germinans require periods of drying (Ning et al., 2003).

It is not currently known how climate change will affect the atmosphere and subsequent terrestrial processes, making the extrapolation of the effects of climate change on mangrove forests increasingly difficult. Precipitation is expected to be spatially variable with increasing climate change and the contrast between wet and dry regions and between seasons is expected to increase (Stocker et al., 2014). The impact of increasing precipitation is expected to have a positive effect on growth rates, biodiversity and mangrove extent as they migrate into previously drier environments (Eslami-Andargoli et al., 2009; Buckney, 1987). An increase in
1.8. MANGROVE DEGRADATION: LOSSES AND CAUSES

Figure 1.7: Expected sea-level rise under the Representative Concentration Pathways (RCPs) of greenhouse gas concentration trajectories. RCP2.6 represents the lowest estimate and RCP8.5, the highest (Stocker et al., 2014).

Figure 1.8: Predicted changes in global average precipitation with projected global warming estimates (Stocker et al., 2014).
precipitation will also decrease the salinity of the environment and is expected to lead to an increase in species richness and diversity (Tomlinson, 1986; Asbridge et al., 2015). In contrast, a decrease in precipitation will increase the salinity of mangrove environments and cause an overall decrease in mangrove area as freshwater influxes become too saline to support growth (Field, 1995; Duke et al., 1998; Gilman et al., 2008). Decreases in precipitation are also likely to cause a reduction in photosynthesis as a consequence of increased aridity (Árreola-Lizárraga et al., 2004). Global changes in average precipitation as predicted by Stocker et al. (2014) are presented in Figure 1.8.

Atmospheric temperatures will increase by as much as 2°C by the end of 2100 and are forecast to increase further thereafter (Stocker et al., 2014). Optimal mangrove growth occurs at an air temperature of approximately 25°C and is generally limited to an air temperature above 15°C (Hutchings and Saenger, 1987). Changes in atmospheric temperature can be expected to cause an expansion of mangroves into higher latitudes and change the species composition and distribution of mangrove forests (Soares et al., 2012; Wilson and Saintilan, 2012; Saintilan et al., 2014). However, this will only be valid until an upper threshold is reached. Increases in temperature above these levels may cause leaf stress, water loss, reduced growth rates and alter species composition (Smith et al., 1989; Saenger, 1982; Clough, 1993). Changes in air temperature on this scale are unlikely to have a large effect on the extent of mangroves as greater fluctuations are experienced on a diurnal scale (Field, 1995). The observed and predicted changes in average surface temperature as predicted by Stocker et al. (2014) are presented in Figure 1.9.

The changes in air temperature and precipitation are ultimately driven by the quantities of CO₂ in the atmosphere. Concentrations of this gas are expected to increase in the coming century (Stocker et al., 2014) and will have a positive impact on mangrove growth as increased CO₂ has been observed to significantly increase biomass, total stem length, branching activity and total leaf area of mangroves (Farnsworth et al., 1996; Ball et al., 1997).
The effects of climate change on mangrove forests are difficult to accurately predict due to the complexity of the natural system and the intricate and complex nature of feedback loops. Furthermore, the estimations of future climate change are based on models of current trends and so the effects that a changing climate will have upon the mangrove forests of the world are also as uncertain. Mangroves also cover a large geographical range and the effects of climate change will vary geographically and will only become truly apparent as the changes occur.

1.9 Policy relevance: requirements and existing data

1.9.1 Policy requirements

Policy and decision makers require accurate information on the extent and changes to mangrove forests. This information is not currently routinely available, despite the changes in extent that have been recorded. To achieve this, data must be available that can satisfy national and international development, implementation and evaluation. In order to do this, the data must be able to address the aims, targets and needs of policy. The primary policies and their targets that a mangrove monitoring system could support are provided in Table 1.8.
Information must be provided on baseline maps of mangrove extent and additional time-series changes, with changing mangrove extent as a consequence of a variety of drivers. This information will be required to fulfil the range of aims and goals of a wide variety of policies and treaties and be able to directly satisfy some of the needs of policy, such as the inventories required by the Ramsar Convention, whilst combining with other information to meet other targets (i.e. maintaining biodiversity).

1.9.2 Existing global products

The provision of data to policy and decision makers is currently limited. There are few global mangrove maps in existence, with only one wholly utilising remotely sensed data \cite{Giri2011}. The work of Giri et al. (2011) used optical data that was inhibited by cloud cover, which led to gaps in the dataset and an incomplete global map. A sufficient quantity of data to achieve a global product using optical data had to be gathered over a number of years, so that the baseline map did not represent a specific point in time. Further to this, the data used was collected in excess of a decade before the baseline was produced, enabling changes in mangrove extent to have occurred without being documented. Previous attempts to this included the conversion of analogue maps to digital format and a number of mangrove forest inventories that lacked information on the spatial extent of the forest \cite{FAO2007,Spalding1997}. Furthermore, there is no current active system in place which can monitor mangrove extent, through the iterative updating of maps generated from time-series remotely sensed data. The major limitations of achieving global products utilising digital data is the applicability of techniques simultaneously across different scales whilst utilising large quantities of data. The development of such techniques is of critical importance if threatened ecosystems such as mangrove forests are to be preserved.
Table 1.8: A number of the policies and treaties that the mapping and monitoring of mangroves is able to directly support.

<table>
<thead>
<tr>
<th>Policy</th>
<th>Policy requirement</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Ramsar Convention</td>
<td>Maps of extent and condition of wetlands and how they change as a result of policy implementation or management responses</td>
<td>[Ramsar 2012, 2005, MacKay et al. 2009]</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>Monitoring, Reporting and Verification of carbon stocks for REDD+ to assist countries in meeting emissions targets committed under the UNFCCC Kyoto Protocol</td>
<td>[Lawrence 2012]</td>
</tr>
<tr>
<td></td>
<td>7: Sustainable use of resources</td>
<td></td>
</tr>
<tr>
<td></td>
<td>11: Conservation of mangrove forests</td>
<td></td>
</tr>
<tr>
<td></td>
<td>14: Restoration of mangrove forests</td>
<td></td>
</tr>
<tr>
<td></td>
<td>15: Enhanced contribution to carbon stocks</td>
<td>[Fatoyinbo and Simard 2013]</td>
</tr>
<tr>
<td>Convention on the Conservation of Migratory</td>
<td>Conservation of migratory species, their habitats and their migration routes and enforcement of legally binding and Memoranda of Understanding (MoU)</td>
<td></td>
</tr>
</tbody>
</table>
1.10 Study aim
To ensure the future preservation of these important ecosystems requires that up-to-date information on changes in their extent are provided to policy and decision makers. The aim of this work is to develop the methods that will form the basis of an operational mangrove monitoring system. This work will highlight the causes and distribution of changes in extent, update the existing mangrove baseline and map changes on both an annual and decadal timescale.

The achievement of this aim would facilitate a mangrove monitoring system that would supply regular data to policy makers and support policy development, implementation and reporting. This would be done through the regular production of maps of mangrove forest extent across the globe, detailing changes in extent and their respective causes.

1.11 Thesis outline
This thesis is presented according to the following structure. Chapter 2 provides a detailed review of the sensors and techniques used for mapping both mangrove forest extent and detecting changes in extent using remotely sensed data. The chapter concludes with the aim and objectives of this study. Chapter 3 introduces each study site used to develop the method of mapping mangrove extent and monitoring change. Chapter 4 provides an overview of the datasets used in the study and their pre-processing. The free and open source software (FOSS) used in this study is also outlined. Chapter 5 provides an overview of the drivers and distribution of changes in mangrove forest extent across the tropics, highlighting regions with the greatest areas of mangrove at risk from degradation and loss. Chapter 6 outlines the approach taken to classify mangrove extent and provides the results and discusses them within the context of the method used. Chapter 7 details the approach to map changes in extent, providing the results and their discussion. Chapter 8 outlines the conclusions of the work and their contribution to an operational mangrove monitoring system.
Chapter 2

Remote Sensing of Mangrove Forests

This chapter reviews the existing literature on mapping mangrove baselines using remotely sensed data. A review of optical and radar datasets is provided, followed by a review of classification techniques and machine learning algorithms. This is followed by a review of methods of change detection using remotely sensed data using map-to-map and image-to-image techniques. The chapter concludes by summarising the knowledge gaps in the field and proposing a number of research questions. Each research question is accompanied by a number of objectives that must be met.

2.1 Remote sensing of mangrove extent and forest structure

Remote sensing provides a means of studying large areas of the Earth’s surface in a time and economically efficient manner. The complex and chaotic nature of mangrove forests with arching aerial prop roots and pneumatophores make travel through a mangrove forest difficult. This limits the area that can be covered by a field survey and subsequently limits the quantity of data that can be collected. Remote sensing provides a solution to this problem, providing data of expansive
areas of mangroves that could not be collected manually. The use of remote sensing has been recognised for this application and a wealth of studies have emerged analysing mangroves across both large temporal and spatial scales. Optical data has been the primary source of remote sensing data used for mapping mangroves although the benefits of microwave remote sensing have become more prominent in recent studies. Remote sensing has been used to map mangroves and retrieve information on their structural attributes across almost their entire range, from small mangrove fringes (Mitchell et al., 2007) to the vast mangrove forests of the Sundarbans (Cornforth et al., 2013). The following section reviews the application of remote sensing for investigating mangroves, discussing the trade-offs between spatial and spectral resolutions and the advantages of utilising wavelengths beyond the visible spectrum.

2.1.1 Optical imagery

One of the initial sources of remote sensing imagery was that acquired by aerial photography. The existing body of literature on the use of aerial photography for mangrove mapping is limited (Green et al., 1998) yet from the little published, the advantages and limitations of using aerial photography are evident. The greatest attribute of aerial photography is the high spatial resolution of the dataset which is far above (5–50 cm) that which can be acquired from spaceborne sensors. This enables a greater number of vegetation classes to be inferred from aerial imagery than can be generated from spaceborne optical data (Sulong et al., 2002) and enables the user to attain detail down to the species and genera level (Sulong et al., 2002; Dahdouh-Guebas and Mathenge, 2000). Furthermore, very detailed structural information can be derived from very high resolution (VHR) imagery, enabling accurate estimations of canopy height to be derived and monitored, if suitable time-series imagery is available (Mitchell et al., 2007, Lucas et al., 2002). Attaining this level of detail can be particularly important in mangrove forests where the early detection of change is important as it can reflect an imminent rapid change in mangrove dynamics. This level of detail, however, is only applicable for a limited extent and is not suitable for mapping large areas, where
data quantity and cost of acquiring and processing data becomes expensive, both economically and in terms of processing time (Harvey and Hill, 2001; Lucas et al., 2002; Green et al., 1998).

Multispectral and hyperspectral data can also be acquired via airborne sensors, providing greater spectral resolution than aerial photography at high spatial resolution (2 m). This higher spectral resolution can be used to attain greater information about the characteristics of mangroves and their canopies by deriving Leaf Area Index (LAI) (Green et al., 1998) and enabling species differentiation (Dahdouh-Guebas and Mathenge, 2000) based upon variations in their spectral reflectance. Imagery of this resolution also enables small localised strips of mangroves to be mapped which may be missed by coarser resolution imagery (Saleh, 2007), can increase classification accuracy by achieving detailed sub-pixel classifications of mangrove forest extent (Kanniah et al., 2007), can attain the detailed mapping of mangrove forest extent down to the species level (Wang et al., 2004) and enable mangrove biomass values to be derived (Proisy et al., 2007). Similarly, hyperspectral data can be acquired via airborne sensors which are able to record data over a wide range of the electromagnetic spectrum (typically Blue to SWIR) but at a far greater spectral resolution than traditional multispectral sensors. Increased spectral detail can be recorded for a range of land cover types, enabling the detailed biophysical attributes of vegetation to be inferred, at a high spatial resolution (Axelsson et al., 2013). The use of airborne hyperspectral imagery to map mangrove forests is poorly represented in the literature, likely a consequence of the advanced techniques required to process hyperspectral imagery, especially for the application of automated classification algorithms (Hirano et al., 2003). Despite this, mangrove extent has been mapped with high accuracies (Yang et al., 2009) and has been used to retrieve chemical concentrations within foliage with varying degrees of certainty (Axelsson et al., 2013).

The primary benefit of airborne data is the acquisition of imagery with a very high spatial resolution. As a consequence accurate digitisation can be carried out
to attain detailed results (Dahdouh-Guebas and Mathenge, 2000) and interpretation cues such as texture and context can be used to enhance and delineate vegetation in wetland environments where vegetation usually forms highly heterogeneous compositions (Harvey and Hill, 2001). Despite this, high resolution datasets are limited by the quantity of data that can be acquired. A greater resolution directly reduces the width of the flight line, requires that a greater number of pixels be analysed to account for the error of even accurate position fixes, produces a smaller signal to noise ratio and requires frequent smoothing to facilitate visual interpretation (Green et al., 1998). Furthermore, the economic cost of acquiring data and the limited ability of airborne sensors to gather data over large geographical areas have likely further limited the widespread use of airborne hyperspectral imagery for mapping mangrove forest extent. These disadvantages prohibit the use of airborne data for the mapping of mangrove forests at the global level, despite the highly detailed results that could be achieved. An overview of the studies that have utilised airborne data for mangrove mapping is provided in Table 2.1.
Table 2.1: A summary of studies that have utilised aerial photography, airborne multispectral and airborne hyperspectral data for mangrove mapping.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Accuracy (%)</th>
<th>Comment</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>High resolution Airborne</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerial Photography</td>
<td>Kemaman, Malaysia</td>
<td>91.2</td>
<td>Higher accuracy than attained from satellite imagery</td>
<td>Sulong et al. (2002)</td>
</tr>
<tr>
<td>CASI</td>
<td>South Caicos</td>
<td>78.2</td>
<td>Predictions of LAI and canopy closure</td>
<td>Green et al. (1998)</td>
</tr>
<tr>
<td>Aerial photography</td>
<td>Northern Territory, Australia</td>
<td>89</td>
<td>Higher accuracy attained with higher resolution</td>
<td>Harvey and Hill (2001)</td>
</tr>
<tr>
<td>UPM-APSB AISA</td>
<td>Selangor, Malaysia</td>
<td>NA</td>
<td></td>
<td>Lucas et al. (2002)</td>
</tr>
<tr>
<td>CASI-2</td>
<td>Brisbane River area, Australia</td>
<td>76</td>
<td>Object-based mapping retrieved greatest accuracy</td>
<td>Kamal and Phinn (2011)</td>
</tr>
<tr>
<td>AISA</td>
<td>Gulf Coast, Texas</td>
<td>95</td>
<td>MNF classifier</td>
<td>Yang et al. (2009)</td>
</tr>
<tr>
<td>HyMap</td>
<td>Berau delta, Indonesia</td>
<td>NA</td>
<td>Retrieval of chemical concentration (e.g., N, Ca, K)</td>
<td>Azelison et al. (2013)</td>
</tr>
<tr>
<td>High Resolution Satellite</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IKONOS/LAI-2000</td>
<td>Brava Lagoon, Mexico</td>
<td>NA</td>
<td>Mangrove health</td>
<td>Kovacs et al. (2002)</td>
</tr>
<tr>
<td>QuickBird</td>
<td>Tecuapan-Agua Brava-Las Haciendas, Mexico</td>
<td>NA</td>
<td>Mangrove condition via LAI</td>
<td>Kovacs et al. (2009)</td>
</tr>
<tr>
<td>IKONOS</td>
<td>French Guiana</td>
<td>(r^2 &gt; 0.9)</td>
<td>Biomass estimation</td>
<td>Proray et al. (2007)</td>
</tr>
<tr>
<td>QuickBird</td>
<td>Ranong Province, Thailand</td>
<td>(r^2=0.65)</td>
<td>Biomass estimation</td>
<td>Hirata et al. (2014)</td>
</tr>
<tr>
<td>IKONOS/QuickBird</td>
<td>Sungai Belungkor, Malaysia</td>
<td>82</td>
<td>Contextual Logical channel classifier</td>
<td>Kanniah et al. (2007)</td>
</tr>
<tr>
<td>IKONOS/QuickBird</td>
<td>Panama</td>
<td>&gt; 70</td>
<td>Maximum-likelihood</td>
<td>Wang et al. (2004)</td>
</tr>
</tbody>
</table>
A major limitation of airborne imagery is the size of the area that can be imaged. Large scale studies using airborne imagery are not viable due to the acquisition of large datasets, often at the expense of spectral resolution. A compromise to maximising both spatial and spectral resolution is to utilise spaceborne data which are capable of acquiring imagery over large geographical areas at medium resolutions (20–30 m). Some spaceborne sensors are able to acquire imagery in wavelengths beyond the near-infrared into short wave infrared wavelengths, measuring more detailed attributes of land cover types than possible with smaller wavelengths.

One of the earliest applications of spaceborne optical imagery specifically for mangrove mapping, was the mapping of mangrove extent in the gulf of Carpentaria, northern Australia, by Long and Skewes (1996). A total mangrove area of 66.25 km$^2$ was successfully mapped. This early work was shortly followed by others, employing more sophisticated mapping techniques. The relationship between Landsat derived NDVI and LAI was modelled to generate a thematic map of LAI for mangroves on the Caicos Bank, Turks and Caicos Islands, attaining an accuracy of 88% (Green et al., 1997). This was followed by sophisticated techniques such as Principal Components Analysis (PCA) and ROC curve techniques that were less dependent upon visual interpretation and were capable of providing information than for a single point in time as time-series data became increasingly available (Ramrez-Garca et al. 1998, Giri and Muhlhausen 2008, Ruiz-Luna and Berlanga-Robles 1999, Berlanga-Robles and Ruiz-Luna 2002, Alatorre et al. 2011). Time-series data can be more readily attained from spaceborne sensors than airborne/VHR imagery due to the consistent acquisition of data that can not readily be achieved via airborne platforms. Time-series studies provide additional information compared to a snapshot of a mangrove forest in time by allowing trends in forest changes to be monitored. This is invaluable information that is able to increase the observation of an environment to the understanding of an environment. These studies on mangrove forests have been well documented at locations including Madagascar, Thailand, Mexico, Kenya and Bangladesh (Giri and Muhlhausen 2008, Giri et al. 2007, Muttitanon and
2.1. REMOTE SENSING OF EXTENT AND STRUCTURE

Tripathi (2005), Vasconcelos et al. (2002), Kirui et al. (2013), Kovacs et al. (2001), Thu and Populus (2007), Conchedda et al. (2008). The coarser resolution of the imagery, however, does not prohibit detailed results from being attained, such as the differentiation of mangrove species (Gang and Agatsiva, 1992). The development of classification algorithms with the continued availability of optical data has enabled increasingly sophisticated techniques of classification to emerge, with the recent increased use of knowledge based approaches and machine learning algorithms (Blasco and Aizpuru, 2002; Gao et al., 2004). Coarser resolution data is available via spaceborne sensors for large area mapping, such as that available from the Moderate resolution Imaging Spectroradiometer (MODIS) which has a spatial resolution of 250 m. The MODIS sensor has a large archive of data and allowed the deforestation of mangrove to be mapped across the Mahakam delta in Kalimantan over a decade (Rahman et al., 2013). Furthermore, data of this resolution enables techniques to be scalable to the global level, especially as sufficient data is available. The first global map of the world derived from remotely sensed data was achieved using a small archive of Landsat data at 30 m spatial resolution.

Similarly, hyperspectral spaceborne imagery is available and although little work had been undertaken into mapping mangrove forests with spaceborne hyperspectral imagery, due to the advanced techniques required to process the data, there are notable successful examples. Demuro and Chisholm (2003) demonstrated that the improved spectral resolution of hyperspectral sensors over multispectral sensors enabled the application of advanced and sophisticated image analysis techniques to discriminate mangrove species, despite the medium pixel resolution of 30 m. The ability to perform advanced image analysis using hyperspectral imagery has been further demonstrated by Chakravortty and Shah (2013), who were able to perform spectral unmixing when species were present not as a homogeneous stand but as a mixed species stand. Through non-linear spectral unmixing, discrete mangrove species were deciphered despite the interaction amongst different endmembers, with a similar approach by Kumar et al. (2013) yielding high accuracies of 96.85% using a machine learning support vector machine (SVM)
approach. Despite the methods available to effectively and accurately derive the required information from spaceborne hyperspectral imagery, the poor representation of such studies in the literature is a consequence of the complexity of the image processing required to derive such information and the unavailability of data at the global scale. A summary of studies that have utilised medium resolution optical satellite data is provided in Table 2.2.

2.1.1.1 Limitations of optical data

A series of limitations restrict optical data from being used as the primary dataset for the remote sensing of wetland vegetation. Primarily, mangrove forests occur across the breadth of the tropics, whereby persistent cloud cover obscures optical imagery. Wetland areas are defined by a complex myriad of steep environmental gradients and as a consequence are composed of a complex heterogeneous mixture of vegetation types. The similarity of the spectral signatures of these vegetation can be difficult to separate and distinguish, even with the use of high resolution hyperspectral imagery (Chakravortty and Choudhury, 2013). The spectral reflectance of a vegetation in the optical portion of the wavelength of the electromagnetic spectrum is defined by its biochemical and biophysical attributes, which are prone to change depending upon a range of external environmental factors. Seasonal environmental change, stresses as a consequence of salinity and disease and the life cycle stage of the vegetation, amongst other factors, are able to influence the biochemical and biophysical characteristics of the vegetation and hence impact the spectral signature of the vegetation.
### Table 2.2: A summary of studies that have utilised medium resolution optical satellite data for mangrove mapping.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Accuracy (%)</th>
<th>Comment</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat</td>
<td>Kenyan coastline</td>
<td>87.5</td>
<td>Underestimation of small fringes</td>
<td>Kirui et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>Dominicas, Guinea-Bissau</td>
<td>86</td>
<td>Mangrove-accuracy (90%)</td>
<td>Vasconcelos et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>Bang Ban Ba, Thailand</td>
<td>95</td>
<td>Maximum-likelihood classifier</td>
<td>Muttitanon and Tripathi (2005)</td>
</tr>
<tr>
<td></td>
<td>Tawi-pan-Ara Bura Lagoon, Mexico</td>
<td>88.5</td>
<td>Undeclared eigenvectors</td>
<td>Kovacs et al. (2001)</td>
</tr>
<tr>
<td></td>
<td>Sungano river mouth, Mexico</td>
<td></td>
<td>Maximum-likelihood classifier</td>
<td>Ramrez-Garca et al. (1998)</td>
</tr>
<tr>
<td></td>
<td>Huizache-Camacho Lagoon system, Mexico</td>
<td>83</td>
<td>ECHO classifier</td>
<td>Ruiz-Luna and Berlanga-Robles (1999)</td>
</tr>
<tr>
<td></td>
<td>Gulf of California, Mexico</td>
<td>84.1</td>
<td>ISODATA hybrid supervised and unsupervised approach</td>
<td>Alatorre et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>Madagascar</td>
<td>84.89</td>
<td>Maximum-likelihood classifier</td>
<td>Giri and Muhlhausen (2008)</td>
</tr>
<tr>
<td></td>
<td>Global</td>
<td>NA</td>
<td>First global map derived from remotely sensed data</td>
<td>Giri et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>Low Casingt, Sundarbans, India</td>
<td>NA</td>
<td>Species differentiation</td>
<td>Conchedda et al. (2008)</td>
</tr>
<tr>
<td></td>
<td>Mela Creek, Kenya</td>
<td>86</td>
<td>Use of quick look data</td>
<td>Giri and Muhlhausen (2008)</td>
</tr>
<tr>
<td></td>
<td>Bay of Bengal</td>
<td>NA</td>
<td>Accuracy improved with spatial knowledge</td>
<td>Rasolofoharinoro et al. (1998)</td>
</tr>
<tr>
<td></td>
<td>Global</td>
<td>83.3%</td>
<td>Species discrimination</td>
<td>Gao et al. (2004)</td>
</tr>
<tr>
<td>Hyperion</td>
<td>Madagascar</td>
<td>NA</td>
<td>Maximum-likelihood classifier</td>
<td>Rasolofoharinoro et al. (1998)</td>
</tr>
<tr>
<td></td>
<td>Minamamura River Estuary, Australia</td>
<td>86-92%</td>
<td>Differentiation of 5 species</td>
<td>Koekin and Vojakas (2013)</td>
</tr>
<tr>
<td></td>
<td>Thaandil, India</td>
<td>NA</td>
<td>Species discrimination</td>
<td>Kumar et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>Sundarbans Ecoregion, India</td>
<td>NA</td>
<td>Species discrimination using SVM</td>
<td>Kumar et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>Biakatama National Park</td>
<td>90.85%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.1. REMOTE SENSING OF EXTENT AND STRUCTURE
2.1.2 Radar imagery

Despite the potential of optical data the restrictions on its use due to its limitations for mapping tropical mangrove forests have been evaluated. Radar data is not impeded by the atmosphere as optical data is and is able to image the Earth’s surface irrespective of cloud cover, enabling data to be consistently acquired. Furthermore, unlike optical data, which measures the surface reflectance of the mangrove, radar can be much more readily interpreted to attain information on the physical properties of vegetation. Its sensitivity to the structure of land cover types has enabled logarithmic relationships between backscatter and above ground biomass (AGB) to be observed with low frequencies determined to be optimal for the estimation of AGB values (Proisy et al., 2003; Mougin et al., 1999; Proisy et al., 2002).

Airborne radar imagery is akin to optical airborne imagery in that it can provide a high spatial resolution dataset over a limited area. The use of airborne radar imagery for mangrove mapping has focused upon the use of the NASA AIRSAR system, capable of gathering radar data in C-, L- and P-band quad-polarization. The primary application of AIRSAR data has not been for the mapping or monitoring of mangrove extent but has been for investigating the interaction of microwave energy with the components of the mangrove forest and the ability to derive relationships between backscatter and biomass (Proisy et al., 2003; Mougin et al., 1999; Proisy et al., 2002). Furthermore, the performance of tonal and textural data for mangrove mapping has been evaluated from airborne SAR, although this study did not provide a map of the complete mangrove system of a given region (Trisasongko, 2009). Attempts to use airborne imagery for mapping mangrove extent have been limited with the notable example of Souza-Filho et al. (2011) who derived strong contrasts between growth stages and healthy and degenerating mangroves achieving maps of extent with user’s accuracies in excess of 90%.

The mapping of large areas of mangrove forest using SAR data has primarily utilised spaceborne imagery. The larger spatial resolution is more adept to the
mapping of large areas than airborne imagery and Earth’s atmosphere does not limit data acquisition. A combination of image segmentation and an object-based classification approach has demonstrated the use of ALOS PALSAR imagery to be successful in separating mangrove from non-mangrove areas, with accuracies up to 92.3%, although accurately mapping different mangrove classes could not be completed to the same accuracy (64.9%) (Flores De Santiago et al., 2013). Further to this, time-series changes in extent have been mapped using ALOS PALSAR (Cornforth et al., 2013) and advanced empirical relationships with fine beam RADARSAT-1 data have been derived between backscatter and the biophysical attributes of LAI, mean stem height, stem density, basel area and mean DBH (Kovacs et al., 2006). The use of radar has also been demonstrated to be capable of species differentiation (Hashim et al., 1999) using JERS-1 and RADARSAT SAR imagery although the data were not used in combination and subsequently suffered poor classification accuracies of 52% and 46% for JERS-1 and RADARSAT, respectively. These works demonstrate the capability of data from a single spaceborne sensor, utilising a range of image analysis techniques and sensors, to successfully map mangrove forests and monitor time-series change in mangrove extent. The number of studies, however, are scant and are restricted by the limited data retrievable from a single-band radar sensor. This has been recognised in the field of radar remote sensing and has subsequently spurred research that utilises a combination of radar with additional radar of a different wavelength or supplementary optical or ancillary data. A summary of satellite radar imagery for mangrove mapping is presented in Table 2.3.
Table 2.3: A summary of studies that have utilised radar satellite imagery for mangrove mapping.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Accuracy</th>
<th>Comment</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALOS PALSAR</td>
<td>Guinea</td>
<td>63.4%</td>
<td>Separation of mangrove into classes</td>
<td>Flores De Santiago et al. 2013</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mangrove/non-mangrove accuracy &gt; 90%</td>
<td></td>
</tr>
<tr>
<td>RADARSAT-2</td>
<td>Sundarbans</td>
<td>N/A</td>
<td>Terrestrial forest not fully separated from mangrove</td>
<td>Kumar and Patnaik 2013</td>
</tr>
<tr>
<td>RADARSAT-1</td>
<td>Mexican Pacific</td>
<td>r² &gt; 0.7</td>
<td>Coefficient of determination for mean stem height</td>
<td>Kovacs et al. 2006</td>
</tr>
<tr>
<td>JERS-1/RADARSAT</td>
<td>Sungai Pulai, Malaysia</td>
<td>JERS-1: 52%, RADARSAT: 46%</td>
<td>Species differentiation</td>
<td>Hashim et al. 1999</td>
</tr>
<tr>
<td>ALOS PALSAR</td>
<td>Sao Paulo, Brazil</td>
<td>85.9%</td>
<td>Frequency-based contextual classification of incoherent attributes</td>
<td>Rocha de Souza Pereira et al. 2012</td>
</tr>
<tr>
<td>ALOS PALSAR</td>
<td>Sundarbans</td>
<td>N/A</td>
<td>Time-series change in extent</td>
<td>Cornforth et al. 2013</td>
</tr>
</tbody>
</table>
The limited number of image bands available with radar imagery advocated the emergence of multisensor studies. These combined radar data of different wavelengths, which were capable of providing information on the structure of land cover types based upon their differing interactions. The majority of mangrove mapping has centred around the use of optical imagery, with little on the use of multimodal data. Early multisensor research on mangroves using radar imagery was conducted by Simard et al. (2002), utilising a novel decision tree classifier combining L- and C-band data, derived from JERS-1 and ERS-1 sensors. This classified the coastal regions of Gabon, which contained a mangrove class, attaining an overall combined accuracy as high as 84%.

Other modes of data have been used successfully in combination with radar, such as the use of hyperspectral CASI data in combination with AIRSAR data to map the mangroves of the Daintree River estuary, North Queensland, Australia. An accuracy of 60.8% was achieved for the separation of the mangrove into broad zones when the CASI data was used in isolation, whilst the AIRSAR data alone yielded a slightly higher accuracy of 66.8%. Through the combination of these datasets, an accuracy of 79.8% was achieved through the use of a hierarchical neural network classification (Held et al., 2003). The combination of spaceborne imagery has been used more extensively than airborne data with Souza Filho et al. (2006) monitoring the shoreline position of the Braganca macrotidal flat of Brazil using a combination of Radarsat radar and Landsat and SPOT optical imagery. Similarly, the major land cover classes of the region were classified by Souza Filho and Paradella (2002) using a combination of Landsat 5 TM and Radarsat-1 imagery although the accuracy of the classification was not provided. A high accuracy, however, was achieved by Ward et al. (2014) in their mapping of the flood inundation and associated vegetation (mangrove) within Kakadu National Park using a combination of ALOS PALSAR and Landsat 5 TM data. They were able to achieve an accuracy of 86% and separate mangroves based upon their varying quantities of biomass. These studies exemplified the benefits of utilising radar and optical data together in order to gather information over a broad range of the electromagnetic spectrum.
Further to this Simard et al. (2008) used radar derived elevation data (SRTM) in combination with spaceborne lidar (ICEsat/GLAS) for the 3D mapping of the mangroves of Cienaga Grande de Santa Marta, Colombia, as well as to derive height and biomass maps of the mangrove forests of Everglades National Park (ENP), Florida (Simard et al., 2006). Through this study, characteristics of mangrove forest biomass and structure over entire forests were retrieved. This approach was similarly utilised by Fatoyinbo and Simard (2013), utilising Landsat ETM+ data to classify mangrove extent, to generate a height and biomass map of mangroves for Africa. These studies utilised radar in a novel manner, combined with additional datasets, to generate height and biomass maps over large geographical areas and further exemplify that a greater variety of data can be generated from using radar datasets in combination with additional data than using radar data alone. A summary of studies that have utilised radar imagery in combination with another mode of data is presented in Table 2.6.

2.1.3 Global assessment of mangrove extent

Independent studies on mangrove forests have often focused on specific regions or specific mangrove forests. This has resulted in studies across the globe, but have not represented global assessments or estimates of mangrove extent. There have been a limited number of global assessments of mangrove extent with a smaller number of these using remotely sensed data to map mangrove forest extent. The earliest estimates of global mangrove cover are those derived for single points in time, with the majority compiled by the FAO (i.e., FAO (2007)). These are composed of national, usually non-systematic, estimates which are revised upon in subsequent reports. Although these are completed with some regularity, the estimates of extent are sometimes conflicting as the method of calculating extent is not robust. These estimates were followed some time later by the ‘World Mangrove Atlas’ produced by Spalding et al. (1997). Optical remotely sensed data was used in-part, alongside existing maps and ground surveys from which mangrove extent was digitised. The utilisation of remotely sensed data in this work was limited, yet produced the first global maps of mangrove forest
extent, with an estimated total mangrove area of 18,100,077 ha over 112 countries. However, atlases such as these suffer from the same limitations as inventories in that they are single snapshots in time. The range of inventories and maps of mangrove extent are given in Table 2.4.

Table 2.4: Existing estimates for global mangrove maps/inventories.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Reference Year</th>
<th>Mangrove Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAO</td>
<td>1980</td>
<td>18,794,000</td>
</tr>
<tr>
<td>Lanjly</td>
<td>1980</td>
<td>15,462,000</td>
</tr>
<tr>
<td>Saenger</td>
<td>1983</td>
<td>16,221,020</td>
</tr>
<tr>
<td>FAO</td>
<td>1980-1985</td>
<td>16,530,000</td>
</tr>
<tr>
<td>FAO</td>
<td>1990-1985</td>
<td>16,925,000</td>
</tr>
<tr>
<td>Groombridge</td>
<td>1992</td>
<td>19,847,861</td>
</tr>
<tr>
<td>ITTO/ISME</td>
<td>1993</td>
<td>14,197,365</td>
</tr>
<tr>
<td>Fisher</td>
<td>1993</td>
<td>19,881,728</td>
</tr>
<tr>
<td>Spalding</td>
<td>1997</td>
<td>18,107,700</td>
</tr>
<tr>
<td>Spalding</td>
<td>2000-2001</td>
<td>15,236,100</td>
</tr>
<tr>
<td>FAO</td>
<td>2000</td>
<td>15,740,000</td>
</tr>
<tr>
<td>Aizpuru</td>
<td>2000</td>
<td>17,075,600</td>
</tr>
<tr>
<td>Giri</td>
<td>2000</td>
<td>13,760,000</td>
</tr>
<tr>
<td>CGMFC-21we</td>
<td>2000</td>
<td>8,349,500</td>
</tr>
<tr>
<td>FAO</td>
<td>2005</td>
<td>15,231,000</td>
</tr>
</tbody>
</table>

Remote sensing affords a method of overcoming some of these limitations, such as inconsistent methods of data recording, as the approach can be systematic across nations. However, these products are not without their own limitations. Common limitations include the lack of adequate spatial and/or temporal resolution. An overview of the limitations of a range of remote sensing approaches is given in Table 2.5.

Table 2.5: Comparison of global mangrove maps derived from remotely sensed data.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Bespoke</th>
<th>Mangrove Class</th>
<th>Resolution</th>
<th>Temporal Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>GlobCover</td>
<td>X</td>
<td></td>
<td>300 m</td>
<td>Coarse (2 studies)</td>
</tr>
<tr>
<td>MODIS Land Cover</td>
<td>✓</td>
<td></td>
<td>250 m</td>
<td>Annual</td>
</tr>
<tr>
<td>GLC 2000</td>
<td>✓</td>
<td></td>
<td>1000 m</td>
<td>Snapshot</td>
</tr>
<tr>
<td>Mangrove Forests of the World</td>
<td>X</td>
<td></td>
<td>30 m</td>
<td>Snapshot</td>
</tr>
<tr>
<td>Global Forest Cover</td>
<td>X</td>
<td></td>
<td>30 m</td>
<td>Annual (2000-2012)</td>
</tr>
<tr>
<td>CGMFC-21we</td>
<td>X</td>
<td></td>
<td>30 m</td>
<td>Annual (2000-2012)</td>
</tr>
<tr>
<td>Mangrove forests distribution of the world</td>
<td>✓</td>
<td></td>
<td>30 m</td>
<td>Snapshot</td>
</tr>
</tbody>
</table>
The first global map exclusive to mangrove forests that utilised remotely sensed data alone was that of Giri et al. (2011). This work utilised over 1000 Landsat scenes gathered over the period 1997–2000, utilising an unsupervised and hybrid-supervised classification algorithm to map the global distribution of mangroves. This work estimated the total mangrove extent to be 13,776,000 ha although the methodology suffered from a number of limitations. Firstly, optical data is degraded by cloud cover and atmospheric effects which would degrade the image and have a negative impact upon the accuracy of the classification. Secondly, as the data was gathered over the period 1997–2000, a baseline for a single point in time could not be derived. Lastly, the work was published in 2011, 14 years after the earliest imagery was acquired and changes in mangrove forest extent would have occurred between this time and the time of publication. Alternative products that incorporated annual estimates of mangrove extent followed, such as the CGMFC-21 (Hamilton and Casey, 2014). These had a much higher temporal resolution but assessed the loss and gain of mangrove within an existing baseline and did not account for the occurrence of mangrove outside of this. Furthermore, the mangrove class was not exclusive to mangroves and was composed of a number of land cover classes.

Traditionally, large scale mangrove mapping was limited to sketch maps, fieldwork maps and the digitising of digital datasets (Spalding et al., 1997). The rapid ascent of spatial technologies as an investigative science has enabled data captured remotely to be used for more efficient and accurate mangrove mapping. Remote sensing is now a primary method through which mangrove extent can be measured and monitored, through a range of modes (Giri et al., 2011). These include passive systems, typically those of airborne and spaceborne optical sensors and active systems such as radar and lidar. As technologies and techniques have improved, it has been possible to measure and model additional properties of mangrove forests in addition to their extent. These include the retrieval of forest structure and estimations of forest biomass (Proisy et al., 2000).
2.2 Classification algorithms

A plethora of algorithms (Simard et al. (2002); Wang et al. (2004); Yang et al. (2009)) have been demonstrated to be capable of mapping mangrove forests that range from the use of both supervised and unsupervised classifiers. This review will focus upon the most recent and commonly used algorithms of machine learning algorithms and knowledge based approaches. A full review of all classification methods can be found in Mather and Tso (2009).

2.2.1 Machine learning algorithms

Machine learning algorithms are those that are able to automatically derive thresholds and subsequently classify remotely sensed data once provided with a training dataset. Machine learning algorithms require little user input and can calculate both probabilistic and hard classes, dependent upon how the algorithm derives thresholds. The most common machine learning algorithm for land cover classification from remotely sensed data has been the maximum-likelihood algorithm. This algorithm is a probabilistic classifier that assigns a pixel to the class into which it has the highest probability of occurring. This requires that the training data for each class is normally distributed so that a probability value can be derived from the mean and covariance of each training class (Lillesand et al. 2014). The maximum-likelihood classifier has been able to achieve moderately high accuracies (70%, Berlanga-Robles and Ruiz-Luna 2002; Ahmad and Quegan 2012) for land cover mapping but is heavily reliant upon the distribution of training data. As a result of this, the maximum-likelihood algorithm has been observed to be outperformed by other algorithms (Li et al. 2012).
Table 2.6: A summary of studies that have utilised radar imagery in combination with another mode of data.

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Sensor</th>
<th>Location</th>
<th>Accuracy (%)</th>
<th>Comment</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>JERS-1/RADARSAT</td>
<td>Sungai Pulai, Malaysia</td>
<td>JERS-1: 52, RADARSAT: 46</td>
<td>Species differentiation</td>
<td>Hashim et al. (1999)</td>
<td></td>
</tr>
<tr>
<td>ERS-1/JERS-1</td>
<td>Gabon</td>
<td>84%</td>
<td>Ensemble decision tree classifier</td>
<td>Simard et al. (2002)</td>
<td></td>
</tr>
<tr>
<td>ERS-1/Landsat</td>
<td>Sunderban</td>
<td>N/A</td>
<td>Manual interpretation</td>
<td>Rao et al. (1999)</td>
<td></td>
</tr>
<tr>
<td>Radarsat/Landsat/SPOT</td>
<td>Braganca, Brazil</td>
<td>N/A</td>
<td>Land cover mapping with multiple mangrove classes</td>
<td>Souza Filho and Paradella (2002)</td>
<td></td>
</tr>
<tr>
<td>ALOS PALSAR/Landsat</td>
<td>Kakadu National Park, Australia</td>
<td>86%</td>
<td>Flood inundation and mangrove differentiation</td>
<td>Ward et al. (2014)</td>
<td></td>
</tr>
<tr>
<td>Radarsat/Landsat</td>
<td>Braganca</td>
<td>N/A</td>
<td>Shoreline position monitoring</td>
<td>Souza Filho et al. (2006)</td>
<td></td>
</tr>
<tr>
<td>ALOS PALSAR/JERS-1/AIRSAR/CASI-2</td>
<td>Multiple distributed sites</td>
<td>N/A</td>
<td>Retrieval of zonation patterns, biomass estimates, structural attributes, change detection</td>
<td>Lucas et al. (2007)</td>
<td></td>
</tr>
<tr>
<td>AIRSAR/CASI</td>
<td>Daintree River, Australia</td>
<td>79.8%</td>
<td></td>
<td>Held et al. (2003)</td>
<td></td>
</tr>
<tr>
<td>SRTM/ICESat/GLAS</td>
<td>Cienaga Grande de Santa Marta, Colombia</td>
<td>height rms=1.9 m</td>
<td>biomass derived from canopy height</td>
<td>Simard et al. (2008)</td>
<td></td>
</tr>
<tr>
<td>SRTM/ICESat/GLAS</td>
<td>Everglades National Park</td>
<td>height rms=2.0 m</td>
<td>biomass derived from stand height</td>
<td>Simard et al. (2006)</td>
<td></td>
</tr>
</tbody>
</table>
2.2. CLASSIFICATION ALGORITHMS

To overcome this, other non-parametric machine learning algorithms are available that do not require that the input data fits a predefined distribution. The most popular of these are Support Vector Machines (SVMs), Random Forests, K-Nearest Neighbour and Artificial Neural Networks (ANNs). Support Vector Machines classify imagery by constructing a hyperplane between classes in the feature space that is the greatest distance away from each class. Untrained pixels are then classified depending on the class to which they are divided into by the hyperplane \((Vapnik, 1999)\). SVMs are able to classify non-linearly separable data by adding additional dimensions into the feature space. Two training classes that are not linearly separable in 2 dimensions may be linearly separable in 3 or more dimensions. The function used to lift the data into a higher dimension is called a kernel. SVMs have been demonstrated to attain accuracies in excess of 70%, reaching values of 90% \((Otukei and Blaschke, 2010)\) \((Petropoulos et al., 2012)\) and to have good generalisation ability. Their primary benefit, however, is their ability to perform accurately with a small training dataset, such as field data that is difficult to collect in a mangrove environment. Despite this, they are limited by their difficulty to parametrise, especially the selection of the most appropriate kernel. The selection of an inappropriate kernel drastically impairs the classification result. \((Shao and Lunetta, 2012)\).

Artificial Neural Networks attempt to mimic the neural networks that occur in nature. They are composed of input and output nodes with a hidden layer of interconnected nodes and neurons. ANNs are capable of being efficient due to the large parallelisation that they are capable of achieving, although designing the architecture can be difficult and requires that a large number of parameters are defined \((Mather and Tso, 2009)\). Despite this, ANNs have been observed to outperform both maximum-likelihood classifiers and SVMs in a land use land cover (LULC) classification of Walneut Creek, Iowa, attaining an accuracy of 85% (kappa 0.75) using Landsat TM/ETM data \((Srivastava et al., 2012)\). Srivastava et al. (2012) acknowledged that ANNs could not be generalised to be a better classifier than SVMs and further application of the algorithms to real world problems was required. This was reiterated by Song et al. (2012) in a com-
parison of SVMs with ANNs for land cover mapping in Yanqing County, Beijing, using SPOT 5 imagery. They concluded that the algorithms were comparable, with SVMs performing marginally better. It was noted that the training time for ANNs and SVMs can be long and with ANNs occasionally suffering from insufficient training data which limits their routine use with remotely sensed datasets and associated field data.

Random Forests is an ensemble learning process whereby multiple decision trees are run in order to gain a greater accuracy than could be obtained from running a single constituent decision tree. The algorithm creates a user defined number of decision trees to classify an unclassified data point and the mode of all of the tree outputs is used to assign it to a final class. The random element of the algorithm is in the random subset of the training data that is used to construct the decision trees. After each random selection and decision tree, the subset is replaced to the training dataset. In this sense the individual trees are weak learners and the random forest is a strong learner (Breiman [2001]). Random Forests is computationally efficient to run and is much more readily parametrised than other machine learning algorithms, such as Support Vector Machines, with as few as a single parameter required in order to run and optimise the classifier (Pal [2005]). The Random forests algorithm can be easily implemented whilst outperforming other machine learning algorithms, as concluded by Fernández-Delgado et al. [2014] through the comparison of a range of algorithms and multiple remotely sensed datasets. High accuracies have been attained using Random Forests to classify sclerophyll forests in Australia, attaining an overall accuracy of 96% (kappa 0.91) and >80% for mapping land cover types in a mountainous region of Colorado (Mellor et al. [2013] Gislason et al. [2006]). A major benefit of Random Forests is the ability to include ancillary information within the training datasets. This was demonstrated by Mellor et al. [2013] who incorporated terrain and climate variables to train the classifier and by Clewley et al. [2015] who used latitude and longitude to overcome the difference in adjacent swathes in radar imagery used for the classification of Alaskan wetlands.
2.2. CLASSIFICATION ALGORITHMS

The \( k \)-NN algorithm classifies unknown pixel values to the nearest number of \( k \) training class values. The classification requires that a user defines the value of \( k \), which is the number of nearest training values across all classes. The proximity is measured by euclidean distance from the unclassified image pixel \( \text{[Mitchell 1997; McRoberts et al. 2002]} \). A \( k \) value of 3 would assign an unknown object to the class represented by the majority of the nearest 3 training points. \( k \)-NN is the simplest of the machine learning algorithms but is increasingly inefficient to run with an increasing value of \( k \). For example in 1 dimension with a \( k \) value of 5 and 1000 data points, the distance travelled to capture 5 data points is 5/1000 (0.005), of the feature space provided that the data are uniformly distributed. In the case of 50 dimensions under the same conditions, to capture the same 5 data points 0.995 of the dimension must be travelled. Therefore, at high dimensions the distance travelled is greater, which can be misleading when only 2 dimensions are useful in classifying the unknown object. This is known as the curse of dimensionality \( \text{[Mitchell 1997]} \). \( k \)-NN has been predominantly used in the classification of Finnish forests where it has been used to estimate stem volume by species group using a forest inventory map in Finland \( \text{[Tokola et al. 1996; Tomppo and Katila 1991]} \). More recently it has been used to estimate and map forest stand density, volume type and cover type featuring weighting parameters, using composite imagery in the US \( \text{[Franco-Lopez et al. 2001]} \) and was used to attain biomass estimates for forest in Canada with an R\(^2\) value of 0.62 ±0.002 \( \text{[Beaudoin et al. 2014]} \). In these studies and in the work of Baffetta et al. \( \text{[2009]} \), \( k \)NN has been demonstrated to be effective in coupling remotely sensed imagery with field data.

2.2.2 Knowledge-based classifiers

Whereas machine learning algorithms are able to automatically learn the knowledge required to attain a classification, predominantly the defining of class thresholds, knowledge based approaches rely upon a user to provide this information. This has the advantage of not requiring training data or the parametrisation of the classifier but suffers the disadvantage of not being able to be run automati-
cally or be reimplemented quickly. The most common knowledge based classifiers are rule based classifiers, commonly accompanied by image segmentation which can be used to apply the user knowledge. An object oriented rule based classification was achieved by the Japanese Aerospace Exploration Agency (JAXA) in the generation of a global forest/non-forest map where simple thresholds were used to differentiate the land cover types [Shimada et al., 2014], using radar data alone. A knowledge-based classifier enables a large number of discrete, continuous and ancillary data to be used. This was exemplified by Lucas et al. (2011) through the updating of the habitat map of Wales, UK. The segmentation of SPOT imagery was aided by Land Parcel Information System (LPIS) boundaries and the rule based classification incorporated topography data, urban and water body data and existing habitat maps, attaining results in excess of 80%. Approaches such as this enable full user control over the classification but are limited in that they are difficult to automate and are, therefore, not appropriate for use over a large number of study sites. A full review of the benefits of an object-based approach is available in Blaschke (2010).

2.3 Detecting change in mangrove forest extent

The classification of mangrove extent is able to provide an areal map of mangrove for a single period in time, providing valuable information on the extent of the forests in a region. In order to provide policy and decision makers with adequate information for the protection and preservation of these ecosystems, however, knowledge on the changes in mangrove forests over time is required. In order to provide this information, regular updates to the classification of mangrove extent are required. This can be achieved through a regular mangrove monitoring system.

Remote sensing provides a means of monitoring changes in mangrove extent, utilising the same benefits of acquiring baseline classifications. Remote sensing imagery is captured regularly providing a means of collecting data over large regions which could not be achieved manually. The collection of remotely sensed
imagery is consistent and repeatable and at scales that are able to discern the effects of natural and anthropogenic changes over large geographical areas.

Change detection using remotely sensed imagery is broadly divided into two categories (Singh, 1989). The first is that of the comparison of independently produced classifications and the second is that of the simultaneous analysis of multitemporal data. These are commonly referred to as map-to-map and image-to-image methods, respectively. The former relies on the comparison of independent classifications to monitor changes in remotely sensed data. The latter does not compare products from data but analyses the remotely sensed data to detect changes in the image pixel/object values. This approach utilises a number of different techniques and variety of image processing algorithms.

### 2.3.1 Map-to-map techniques

The primary benefits of map-to-map methods are that, as the remotely sensed data are classified separately, the radiometric calibration between images is not important and the results can be tailored to omit classes that are of no interest. Furthermore, through the labelling of the classification classes, a full matrix is retrievable detailing the changes between classes (Singh, 1989; Coppin et al., 2004). Examples of map-to-map methods have been demonstrated by Alesheikh et al. (2007) and Walter (2004) using products within a GIS to map changes in coastlines and the use of probabilistic classification algorithms (maximum-likelihood) to classify changes in land cover maps. A fundamental limitation of the post-classification method of detecting change is that the accuracy of the output is a product of the accuracy of the input data. This accuracy is often equitable to the multiplication of the individual accuracies. Post-classification methods, therefore, require that two reliable and accurate classifications can be sourced, potentially for a number of iterations in the example of a continuous monitoring system. Although accurate results were achieved via these methods, map-to-map approaches to change detection are inappropriate for this present study. A baseline mangrove classification is available for 2010, yet insufficient data is available for the classification of mangrove extent at another point in
time. It is, therefore, not feasible to generate a second baseline map of mangrove extent for use within a map-to-map approach.

2.3.2 Image-to-image techniques

2.3.2.1 Image differencing

As a consequence of the limitations associated with generating consistently accurate classifications for post-classification analysis, the detection of change features from multi-temporal imagery is preferable and capable of attaining greater accuracies (Macleod and Congalton, 1998). The most common method of retrieving change features from imagery is that of image differencing.

Univariate image differencing is the process of subtracting the values in one image, \( t_1 \), from those of a second image, \( t_2 \). On the premise that the two images are perfectly co-registered, both radiometrically and geometrically, the resultant image will be composed of zero values that constitute areas of no change and both positive and negative values that constitute change features (Coppin et al., 2004). A primary limitation of such an approach is in obtaining two perfectly co-registered and atmospherically corrected images, although the requirement for atmospheric correction can be remedied in part by using spectral indices (Lyon et al., 1998) rather than direct spectral reflectance values. Furthermore, the threshold on which change detection should be applied is difficult to automate, despite attempts to both manually and automatically locate thresholds using \( k \)-means clustering (Celik, 2009) and Bayesian decision theory in combination with Markov Random Fields (MRF’s) (Bruzzone and Prieto, 2000, 2002). Despite attempts to remedy these, the approaches are limited in that the change detection cannot be applied between different sensors due to the difference in sensor characteristics and calibration. A further persistent limitation of such approaches is that the method detects change features within an image whereby the land cover classes are unknown and the approach cannot be applied to a class of interest but to detect changes across all pixels in the scene. This method, therefore, would not be able to make use of the classification of the mangrove baseline and as a result
of this, the change categories would be limited to that of ‘change’ and ‘no-change’ and would not provide any information on the change trajectory. Furthermore, this study is relying upon the use of radar data which is not appropriate for use within image differencing techniques due to the speckle in the imagery. As the earliest radar imagery was collected by a different sensor (JERS-1) than the most recent imagery (ALOS PALSAR), it cannot be ensured that the radar imagery are calibrated to one another for effective and accurate image differencing to be implemented.

### 2.3.2.2 Image ratioing

More suited to SAR imagery is that of image ratioing, whereby unlike image differencing, one image $t_1$ is divided by another, $t_2$. Pixel values that are unchanged will have a value of one and pixels that have undergone change will have a value greater or less than one. This method suffers from the same limitations as image differencing, as the two images need to be perfectly calibrated and co-registered in order for change and unchanged pixels to be separated. The selection of a threshold also poses a substantial challenge, as the change features create a bimodal non-Gaussian distribution and subsequent thresholds implemented using the mean and standard deviation of the distribution are inherently flawed (Alqurashi and Kumar 2013; Coppin et al. 2004). Limited studies have been carried out by Howarth and Wickware (1981) but other methods such a vegetation index differencing were found to outperform image ratioing (Nelson 1983), particularly for use with optical data. The major limitation of implementing image ratioing is that the two images acquired on separate dates need to be collected from the same sensor so that differences in preprocessing, calibration and normalizing between images can be avoided (Moser and Serpico 2009).

### 2.3.2.3 Change Vector Analysis (CVA)

Change vector analysis is a means of detecting change features using both the magnitude and direction of the potential change event in the feature space. The total magnitude can be determined from the Euclidean distance between two points in an $n$-dimensional feature space (Alqurashi and Kumar 2013). A major
benefit of CVA is that it is capable of concurrently analysing a change event in all data layers provided and not just selected bands (Coppin et al., 2004). CVA has been demonstrated to achieve accurate results exceeding 95% (Chen et al., 2003) and kappa coefficients of 0.91 (Xian et al., 2009). Although advancements have been made in the field, CVA remains a complex and challenging method to implement that requires well registered data, preferably obtained from the same sensor.

2.3.2.4 Image transformation

Bi-temporal linear data transformations aim to utilise imagery in combination as opposed to their product (Coppin et al., 2004). This is commonly done by stacking the imagery in 2n-dimensional space. The most common image transformation is that of principal component analysis (PCA). In this case the major components account for variation that is not due to land cover change and the minor components account for land cover changes by enhancing the spectral contrasts between the two image dates. Collins and Woodcock (1996) compared the use of PCA with two other transformation techniques, namely multitemporal Kauth-Thomas Transformation (MKT) and Gramm-schmidt Orthogonalization (GS), with the PCA and MKT methods outperforming the GS.

Tasselled cap transformation is another form of image transformation that reduces the spectral bands of Landsat imagery into three orthogonal indices called brightness, wetness and greenness. Whilst it has been shown to be effective at detecting changes that occur over long periods (8-year monitoring cycles) the method is applicable to optical imagery only. Similarly, linear spectral unmixing has been used for detecting change within optical remotely sensed imagery (Mucher et al., 2000) but the use of radar imagery as the primary dataset in this study limits its implementation. Similar to image transformation is image correlation which assumes that image pixels from bi-temporal images are correlated when no change occurs and are uncorrelated when change has occurred within the pixel (Im et al., 2008). This provides additional useful contextual features to aid classification when spectral bands are limited.
2.3. DETECTING CHANGE IN MANGROVE FOREST EXTENT

2.3.2.5 SAR specific techniques

Although a number of image differencing techniques have been established, these are often only for optical datasets. Optical imagery is more widely used within remote sensing and there is a greater abundance of available imagery, especially that for time-series analysis, than radar imagery. However, the successful launch of ALOS-2 and Sentinel-1 demonstrate the intention for the increased use of radar within remote sensing, as complexities surrounding the use of the data are diminishing. This increasing use of radar remote sensing for change detection is able to make use of a number of properties of radar imagery that have benefits over equivalent optical imagery. Radar imagery can be captured irrespective of illumination or atmospheric conditions, so imagery can be acquired over high latitudes during winter months and over areas with near constant cloud cover. This provides an archive of data with regularly available and usable scenes, that is not be guaranteed with optical datasets.

The majority of literature surrounding change detection using remotely sensed radar imagery is concentrated around the development of algorithms and methods with few applications where the methods have been consistently used. Difference imaging is not regularly implemented as a change detection method using SAR imagery but was modified by [Gong et al., 2012] who introduced a neighbourhood-based ratio operator to produce a difference image that utilises a combination of grey level and spatial information of neighbour pixels. However, due to the multiplicative nature of speckle, image differencing is often deemed inappropriate and image ratioing is instead considered more effective at comparing two SAR temporal images ([Rignot and Van Zyl, 1993; Villasenor et al., 1993]).

The majority of the literature has focused upon ratio imaging yet [Bazi et al., 2005] identified that the automatic unsupervised implementation of SAR detection within radar imagery is still withheld as issues of image despeckling, choice of comparison operator and optimal threshold selection still need to be overcome. This has been addressed through techniques to reduce image speckle ([Bovolo and Bruzzone, 2005]) using a wavelet-based multi-scale decomposition of the log-
ratio image. Optimal threshold detection has been sought by Moser and Serpico (2006) using the Kittler-Illingworth minimum error thresholding algorithm to overcome the often non-Gaussian distribution of SAR amplitude values although they do not apply their method to an operational application whilst Ban and Yousif (2012) used the algorithm to model the distributions of the change and no-change classes and achieve a threshold. Automated thresholding, however, assumes that the pdf of the change class is known, limiting the unsupervised applicability of the method. Many change detection algorithms using radar have been implemented as part of an experimental approach and not within the context of an application. These methods are rarely fully developed and as a consequence are difficult to implement (Carincotte et al. 2006).

2.4 Research questions and objectives

Despite the information attained through the use of remote sensing for studying mangroves, persistent gaps in the knowledge and understanding of their extent and the drivers of its change remain. These gaps consist of knowledge on the global distribution of drivers of change, an up-to-date baseline and a method of routinely monitoring changes in extent.

Information on the causes and distribution of the drivers of change in mangrove extent is of critical importance. The largest drivers of change have been inferred from discrete studies on mangrove extent but the distribution of all causes of change have not previously been graphically represented. Without this knowledge, the effect of the drivers of change upon mangrove extents at the global level cannot be fully comprehended.

A number of global mangrove maps and inventories have been generated as the importance of mangrove forests for maintaining wider ecosystem function has become more evident, yet these are primarily limited to representing a mangrove extent for a single point in time. These baselines are often composed of data that transcends multiple years of data and are often generated using a method that cannot be readily repeated with high temporal resolution. This is especially
pertinent for existing methods of change detection that cannot currently be automated and require either multiple baselines to be achieved or that only enable the detection of changes that are not class specific. There is currently, therefore, no monitoring system in place that is able to regularly update the global mangrove extent. This is a function of the lack of a method that is able to generate a complete global mangrove baseline and detect changes in an automated manner.

The aim of this study is to address these shortcomings by fulfilling the following research questions.

1. What is the current distribution and the causes of change in mangrove forest extent across their range?
   (a) Utilise time-series cloud free colour composite radar imagery to provide an overview of the changes in global extent over a large temporal timescale.
   (b) Identify changes in mangrove extent and derive categories of change.
   (c) Graphically display the distribution of the drivers of change in their extent.
   (d) Retrieve information on both global and regional distribution and causes of change.

2. What is the current global extent of mangrove forests?
   (a) Utilise a combination of radar and composite optical imagery to map mangrove forest extent using a repeatable method.
   (b) Utilise a range of mangrove environments to ensure global applicability of the method.
   (c) Improve existing global maps to aid the collection of training data.
   (d) Utilise a machine learning algorithm to classify mangrove forest extent.

3. How have mangrove forests responded to drivers of change? Can these
changes be monitored in an automated manner?

(a) Develop an automated method of change detection without the limitations of a map-to-map or image-to-image technique.

(b) Map changes in extent caused by a number of drivers.

(c) Monitor change over periods ranging from 1 to 14–years.

(d) Calculate gains and losses in carbon that accompany changes in mangrove forest extent.
Chapter 3

Study Locations

This chapter introduces the study sites used in this body of work. The criteria on which the study sites were selected is outlined before each site is described in detail. The location of each site is provided alongside a description of the mangrove forests they contain and the characteristics of the surrounding environment.

3.1 Study site selection criteria

Mangrove environments are not globally homogeneous and vary with both latitude and longitude. The extent of mangrove forests are dictated by the limits of saline water in which they are physically adept to growing. Their distribution is further dictated by the geomorphological settings and climate of their environment. As a consequence, mangroves may occur in large continuous forest blocks or be limited to narrow fringes and isolated and fragmented stands. The surrounding environment may be composed of tropical rainforest, savannah vegetation or large expanses of bare mud/saltflats. Further to this the region may or may not have experienced a change in extent, influenced by either natural of anthropogenic processes. In order to develop a method capable of monitoring mangroves across the globe, it is imperative that they are represented by a variety of types, settings and change processes.
To develop a method of updating the mangrove baseline and monitoring changes in extent across the globe, the study sites must exhibit changes in extent that are driven by a range of processes. These may be natural or anthropogenic drivers. Further to this, mangrove forests can vary in type and surrounding environment and so it is important that sufficient sampling of these is achieved in order to develop a globally applicable method. This negates the need for multiple methods, such as regionally specific ones, enabling a more efficient monitoring system to be developed. In order to achieve this, different mangrove forests at multiple locations must be used as study sites that cover the variation of known change in mangroves across the globe. The study sites were chosen using a combination of sites sourced from the literature and use of expert knowledge. The diversity in the criteria on which the study sites were chosen is outlined below and is provided in Table 3.1.

### Surrounding Environment

The surrounding environment is of importance as adjacent land cover types may be causes of class confusion. This would be more likely to occur at locations where mangrove transitions to tropical rainforest due to similarities in spectral reflectance and backscatter than at locations where mangrove is backed by open saltflats, but it is important that all surrounding environments are sampled.

### Dominant Species

It is important that the method is not sensitive to mangrove species and that the mangrove forest is classified as a land cover type and not by species. This was achieved by Giri et al. (2011) demonstrating that mangrove forests could be classified to a single class. In order to ensure this, the selection of study sites must represent a range of mangrove species and associate species.

### Forest extent

The forest extent criteria is used to ensure that different forest stand types are adequately represented. These may vary from large forest stands to
3.1. STUDY SITE SELECTION CRITERIA

small fine coastal fringes and islands. The method must be able adaptable
to the range of naturally occurring mangrove stand types that are a function
of their environmental setting.

Forest Setting

Hogarth (1999) outlines that mangrove zonation and succession are a func-
tion of their environment which may not be visible as it may not follow the
traditional model of succession from the coast to inland climax vegetation.
It is common for young mangrove to occur at either or both the landward
and seaward margin of the forest. The forest setting will, therefore, dictate
the species composition and growth succession of the mangrove and it is
important that the method is able to classify mangrove forests defined by
a range of settings as this could control that changes that occur to it. Two
examples of this setting would be deltaic or estuarine.

Fragmentation

This criteria represents the continuity of the forest which may be a contin-
uous expanse, whether it be a large stand or a fine fringe, or a mangrove
forest that has been naturally or anthropogenically fragmented. This cate-
gory is important as some regions have pristine expanses of mangrove whilst
others have been heavily anthropogenically changed. A range of fragmenta-
tion in this category will ensure that the method is able to classify both
continuous stands and isolated fragments with the same accuracy. This
criteria may reveal a minimum fragment size that can be reliably classified.
Also, as anthropogenically fragmented locations are of interest for monitor-
ing in terms of highlighting the most threatened regions, the capability to
accurately represent them is of critical importance. A monitoring system
must be able to adequately monitor these changes which drive the forest
fragmentation.

Condition

This criteria assesses the condition of the mangrove forest as to whether
it has experienced any form of change in extent. Forests that show no
sign of change are labelled as pristine whilst others are categorised by the nature and scale of the change that has occurred, whether it be naturally or anthropogenically driven. Small natural changes is change that has affected little of the mangrove in the region, which may be associated with the change in extent of an isolated part of the mangrove extent. Large natural change is that which has occurred over a large area of the extent and along large portions of the coastline. Anthropogenic disturbance defines change that has occurred due to anthropogenic influence, such as logging. This is important as the information on the human influence upon the natural environment is required by policy makers. This is an important criteria as an operational monitoring system will have to detect changes in mangrove extent that are caused by a number of drivers as well as be resilient to the false detection of changes in pristine environments.

3.2 Study site locations

The following study sites (3.1) were chosen as they each offer an important variation in the criteria that must be considered in the development of a mangrove monitoring system that is applicable to mangroves over a wide range of environmental settings, forest types and processes of change. These sites provide a diverse range of categories within the selection criteria so that the classifier and change detection method are capable of retrieving accurate results, despite their variation. To develop a system that is globally applicable will require that all of these factors are adequately accounted for. The individuality of the study sites empowers them as a collective on which to develop an accurate monitoring system.

Sixteen study sites were chosen, composed of 42 ALOS PALSAR 1° × 1° scenes. The regions were distributed across the tropics with 1 located in Central America, 8 in South America, 3 in Africa, 3 in Southeast Asia and 1 in Australia. A description and map of each study site is provided, alongside the justification for the selection of each site. The study sites are grouped by geographical region.
Table 3.1: The categories of change on which the study sites were selected, alongside the variation in a number of criteria. The primary categories of change were anthropogenic disturbance, small natural change, large natural change and pristine.

<table>
<thead>
<tr>
<th>Number</th>
<th>Study Site</th>
<th>Coordinates</th>
<th>Surrounding Environment</th>
<th>Dominant Species</th>
<th>Forest Extent</th>
<th>Forest Setting</th>
<th>Fragmentation</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Fronesca</td>
<td>13°23'–12°50'N, 87°35'–87°20'W</td>
<td>open mudflats and agri/aquaculture</td>
<td>Rhizophora mangle, Avicennia germinans, Laguncularia racemosa</td>
<td>coastal fringes</td>
<td>Estuarine</td>
<td>Continuous stands fragmented in places</td>
<td>Anthropogenic disturbance</td>
</tr>
<tr>
<td>2.</td>
<td>Bragantina</td>
<td>0°80'–1°07'S, 46°76'–46°52'W</td>
<td>Tropical Savannah</td>
<td>Rhizophora mangle, Avicennia germinans</td>
<td>Limited on peninsulas within close proximity to the coast</td>
<td>Coastal</td>
<td>Continuous stands</td>
<td>Small natural change</td>
</tr>
<tr>
<td>3.</td>
<td>Sao Lus</td>
<td>2°06'–3°18'S, 44°00'–44°48'W</td>
<td>Arid/Tropical Savannah and wetlands</td>
<td>Rhizophora mangle, Avicennia germinans</td>
<td>Large and small fringes along a river estuary</td>
<td>Riverine/estuarine</td>
<td>Continuous stands</td>
<td>Large natural change</td>
</tr>
<tr>
<td>4.</td>
<td>Amazon</td>
<td>08°20'–01°40'N, 49°54'–51°06'W</td>
<td>Savannah and riparian forest</td>
<td>Rhizophora mangle, Laguncularia racemosa</td>
<td>Coastal</td>
<td>Continuous stands and fringes</td>
<td>Pristine</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>Todos o</td>
<td>12°36'–13°39'S, 38°27'–38°38'W</td>
<td>Tropical vegetation on elevated slopes</td>
<td>Laguncularia racemosa</td>
<td>Fine fringes that line river banks</td>
<td>Estuarine</td>
<td>Isolated fragmented extents</td>
<td>Small natural change</td>
</tr>
<tr>
<td>6.</td>
<td>Guayaquil,</td>
<td>2°30'–3°30'S, 79°40'–80°20'W</td>
<td>Arid Savannah and agriculture</td>
<td>Avicennia germinans, Rhizophora mangle</td>
<td>Large stands with Limited fringes</td>
<td>Estuarine</td>
<td>Fragmented by aquaculture</td>
<td>Anthropogenic disturbance</td>
</tr>
<tr>
<td>7.</td>
<td>Puerto</td>
<td>5°45'–4°10'N, 53°55'–51°35'W</td>
<td>Tropical rainforest</td>
<td>Laguncularia racemosa, Avicennia germinans, Rhizophora mangle, Rhizophora racemosa</td>
<td>Coastal fringes</td>
<td>Coastal</td>
<td>Continuous stands</td>
<td>Large natural change</td>
</tr>
<tr>
<td>8.</td>
<td>Venezuela</td>
<td>10°28'–10°50'N, 60°54'–62°39'W</td>
<td>Tropical rainforest</td>
<td>Not available</td>
<td>Coastal fringes</td>
<td>Coastal</td>
<td>Continuous stands</td>
<td>Large natural change</td>
</tr>
<tr>
<td>9.</td>
<td>Guinea</td>
<td>5°45'–4°10'N, 53°55'–51°35'W</td>
<td>Arid Savannah</td>
<td>Rhizophora mangle, Laguncularia racemosa, Avicennia germinans</td>
<td>Large and small riverside fringes</td>
<td>Coastal/riverine</td>
<td>Continuous and fragmented stands</td>
<td>Large natural change</td>
</tr>
<tr>
<td>10.</td>
<td>Mozambique</td>
<td>17°00'–18°00'N, 36°00'–38°E</td>
<td>Tropical Savannah</td>
<td>Avicennia germinans, Rhizophora mangle, Bruguiera gymnorhiza, Heritiera littoralis</td>
<td>Riverine fringes</td>
<td>Riverine</td>
<td>Naturally fragmented</td>
<td>Pristine</td>
</tr>
<tr>
<td>11.</td>
<td>Niger Delta</td>
<td>4°16'–5°33'N, 6°05'–6°31'E</td>
<td>Tropical savannah</td>
<td>Avicennia africana, Rhizophora racemosa, Avicennia germinans, Rhizophora mangle, Bruguiera gymnorrhiza</td>
<td>Large forest stand</td>
<td>Deltaic/coastal</td>
<td>Continuous forest</td>
<td>Pristine</td>
</tr>
<tr>
<td>12.</td>
<td>B aggregation and peatland</td>
<td>Not Available</td>
<td>Laguncularia racemosa</td>
<td>Not Available</td>
<td>Coastal island and riverine fringes</td>
<td>Coastal/riverine</td>
<td>Continuous stands</td>
<td>Large natural change</td>
</tr>
<tr>
<td>13-14.</td>
<td>East Kalimantan, Indonesia</td>
<td>0°00'–2°00'S, 116°00'–118°00'E</td>
<td>Agriculture and tropical savannah</td>
<td>Avicennia sonneratia, Rhizophora stylosa, Xylocarpus sp, Nypa sp</td>
<td>Large forest stand</td>
<td>Deltaic</td>
<td>Heavily fragmented</td>
<td>Anthropogenic disturbance</td>
</tr>
<tr>
<td>15.</td>
<td>Penang, Malaysia</td>
<td>4°00'–5°00'N, 100°00'–101°00'E</td>
<td>Urban and agriculture</td>
<td>Rhizophora apiculata, Avicennia alba, Rhizophora stylosa, Bruguiera gymnorhiza, B. parviflora</td>
<td>Large forest stand</td>
<td>Coastal</td>
<td>Fragmented by logging</td>
<td>Anthropogenic disturbance</td>
</tr>
<tr>
<td>16.</td>
<td>Kakohi, Australia</td>
<td>12°00'–13°00'S and 13°00'–13°30'E</td>
<td>Arid Savannah</td>
<td>Sonneratia alba, Rhizophora stylosa, Avicennia Marina</td>
<td>Coastal and riverine fringes and islands</td>
<td>Coastal/riverine</td>
<td>Naturally fragmented</td>
<td>Pristine</td>
</tr>
</tbody>
</table>
CHAPTER 3. STUDY LOCATIONS

3.3 Central America

3.3.1 Gulf of Fonseca, Honduras

The Gulf of Fonseca (13°23’–12°50’N, 87°53’–87°10’W) is located at the intersection with Honduras, El Salvador and Nicaragua (Figure 3.1) on the western coast of Central America. The Gulf of Fonseca is a drowned river valley type estuary, composed of mud flats and shoal areas, fragmented by extensive interdistributary tidal channels with a total coastal area of approximately 100 km². The climate is characterized by distinct dry and wet seasons with an annual precipitation range of 1,500–2,000 mm with a mean annual temperature of 30° C. The average tidal range in the region is 2.3 m. The dominant species of mangrove in the region are Rhizophora mangle, Avicennia germinans and Laguncularia racemosa (Castañeda-moya et al. 2006, Dewalt et al. 1996). The mangroves of the Gulf of Fonseca form continuous stands in the northern part of the gulf but are limited to tidal creeks in the southern region of the gulf. A rapid increase in shrimp ponds in the region from the early 1980s has caused the loss of 6,760 ha or 22 % of the mangrove forest that existed in 1973 (Dewalt et al. 1996). Aquaculture ponds have been installed amongst the stands of mangrove in the northern region whilst the creeks of the southern region have been altered as aquaculture ponds have been installed within the mudflats on the landward side of the mangrove fringes. The mangroves have also been encroached upon by agriculture in the region.

The Gulf of Fronesca was chosen as it has a complex environmental setting and anthropogenic induced change that a monitoring system must be adept to classifying. The landward margin of the mangrove is limited by agriculture in the West of the site but can grow into mudflat/saltpan and in the East, despite the installation of aquaculture in the last 30 years. This provides the opportunity to classify detailed dendritic mangroves and monitor both advances of new mangrove and also losses from encroaching aquaculture.
Figure 3.1: The study location in central America on the southern coast of Honduras. The mangroves of the Gulf of Fonseca in the insert, shows the mangroves in the region in continuous stands (Giri et al., 2011). The mangroves in the east of the region are disrupted by heavy aquaculture in the region. Made with Natural Earth.
3.4 South America

3.4.1 Para State, Brazil. The Bragantina coastline and Sao Luis

Para State, Brazil, has a coastline of mangrove forest that compose two study sites in this work. The first is the mangrove forest surrounding Sao Luis (Figure 3.2) whilst the second is the mangrove forest of Braganca (Figure 3.3). The two mangrove forests are part of the same continuous mangrove belt and an overview of the region is provided for both.

The peninsula of Braganca (0°80’–1°07’S, 46°76’–46°52’W) is situated between the estuaries of the Caete and Tapera-Acu rivers on the northern Atlantic coast of Brazil. The mangroves of Sao Luis are south of the estuary of the Tapera-Acu river on surrounding river banks around the city of Sao Luis. The regions are within the Inner Humid Tropics and have a distinct dry season and wet season. The former lasts from June through to December whilst the latter extends from January to May, with annual rainfall ranges between 1,085 and 3,647 mm. The average annual temperatures in the region range from 25.2°C–27.4°C with variations in humidity in 60–91%. The Braganca peninsula is approximately 180 km² of which 90% is covered with mangrove. Species of *Rhizophora mangle* and *Avicennia germinans* dominate this with rare occurrences of *Laguncularia racemosa*. The entire peninsula is not regularly flooded but creeks are flooded regularly by neap tides of 2–3 m and spring tides of 3–4 m (Krause et al., 2001). In the surrounding 180 km² live approximately 13,000 people, of which in excess of 80% derive their livelihood from the mangrove, primarily through small-scale fisheries (Glaser, 2003). Both regions are relatively undisturbed by anthropogenic influence with few settlements amongst the Bragaca mangroves, whilst the city of Sao Luis is prominent yet divided by intact reaches of mangrove forest. Outside of the mangroves, agriculture is widespread at Braganca and extends up as far as the mangrove forest edge. Agriculture is also common around the city of Sao Luis, although the wider area is less affected by agriculture but is a patchwork
of deforestation, pasture and regrowth forest. These practices extend to the mangrove edge but have had little impact upon the mangrove extent in the region. The mangroves are interspersed with bare regions of salt flats with homogeneous stands that give way inland to savannah vegetation and bare soil where the land is out of the reach of the tide. This eventually gives way to the rainforest of the Brazilian Amazon.

Bragantina was chosen as its environmental setting is important in defining the extent of the mangrove. It is a continuous forest across a large geographical area but contains detailed reaches inland along rivers. The classifier must be adept to simultaneously classifying both of these forest extents. The change in extent at Bragantina is due to coastal processes of erosion ad deposition. Sao Luis, in contrast, is largely a riverine environment with some wetlands and associated riparian vegetation. The mangrove is more restricted from going inland than at Braganca with numerous mangrove stands along creeks and rivers. A small area of additional continuous forest enables one study site to represent a range of adjacent mangrove forest extents. This site provides a complex mix of mangrove settings with both coastal and riverine processes that cause natural changes in extent. The system must be capable of classifying and monitoring such complex environments.
Figure 3.2: The Bragantina coastline on the northern coast of Brazil at the mouth of the Amazon River. Insert shows the mangroves in the region on peninsulas mapped by Giri et al. (2011). Made with Natural Earth.
Figure 3.3: The location of the mangroves of Sao Luis on the northern coast of Brazil, south of the Amazon River mouth. Insert shows mangroves on islands in the river and wetland areas along the coast as defined by Giri et al. (2011). The mangrove is interspersed with dry areas of land used for urban areas and agriculture. Made with Natural Earth.
3.4.2 Amapa State, Brazil

The study site of Amapa state covers the extent of Maraca Island and adjacent coastline (Figure 3.4). Maraca Island is a continental island situated between Cape Orange and Cape North (04°20’N–01°40’N, 49°54’–51°06’W). The region has a hot and humid climate, with a mean annual precipitation of approximately 3,250 mm. The elevated regions are not regularly flooded but are inundated with spring tides. The study site is dominated by four species of mangrove; Rhizophora mangle, Rhizophora harrisonii, Avicennia germinans and Laguncularia racemosa (Fernandes, 1999). The mangroves of Amapa state occur in relatively small pockets and fringes along the coastline of Brazil with few large extended forests. The mangroves are undisturbed by anthropogenic activity with roads and urban areas typically 20 km from the mangrove. The mangrove often rapidly turns to savannah, composed of savannah vegetation and patches of bare ground, out of reach of tidal inundation.

Amapa state was chosen as it contains a predominantly large mangrove forest that transitions to another wetland forest type with additional small fringes along the coastline. These are two contrasting forest extents although both are dominated by the coastal forest setting. It is imperative that the method is able to accurately map them and distinguish them from similar forest types.
Figure 3.4: The mangroves of Amapa State and Maraca Island, north of the Amazon River mouth. The insert show the mangroves as defined by Giri et al. (2011) confined to pockets along the coast with the surrounding area composed of arid land and savannah vegetation. Made with Natural Earth.
3.4.3 Todos os Santos Bay, Brazil

Baia de Todos os Santos (BTS, $12^\circ36'–13^\circ09'S$, $38^\circ27'–38^\circ38'W$) is the second largest coastal bay in Brazil covering 1,223 km$^2$ with an average depth of 9.8 m. It is located in southeastern Brazil near the large city of Salvador (Figure 3.5). The circulation within the bay is driven by the tides but the water properties are altered by the varying wet and dry seasons. The climate of the bay is tropical humid with an annual mean temperature of 25.3°C and annual mean precipitation of 2,086 mm (Cirano and Lessa, 2007). The intertidal area of the bay is 327 km$^2$ (27%) of which 152 km$^2$ is covered by mangrove. The most common mangrove species in the bay is *Laguncularia racemosa* and accounts for 81% of the mangrove area of the bay (Genz et al., 2006).

Historically, the region was covered in dense tropical rainforest and mangrove but the arrival of the Portuguese caused the conversion of the land for the cultivation of sugar cane and urban settlements (Hatje and Barros, 2012). Since 1550 the area has undergone increasing industrialisation and exploitation so that now 29 industries drain their waste into the bay (Venturini and Tommasi, 2004). This waste, particularly that of oil pollution and heavy metal effluent, has polluted the soils and water in the bay and has been associated with reducing the biomass of *Rhizophora* mangrove and causing mangrove mortality (Orge et al., 2000). The mangroves in the region occupy low intertidal areas within the region, often contained by areas of higher elevation. They are frequently disrupted by infrastructure although much of the mangrove in the region has been left undisturbed.

Todos os Santos was chosen as it represents an estuarine environment with mangroves that are limited to small narrow dendritic extents along rivers. The topography of the region prevents the formation of large forests. A monitoring system must be able to accurately map this detail and differentiate it from surrounding tropical vegetation. These extents are stable having been previously disturbed and provide an opportunity to map isolated and narrow extents whilst being impervious to the detection of false changes.
Figure 3.5: The mangroves of Salvador in southern Brazil. The insert shows the mangroves around Salvador (Giri et al. 2011), confined to the coast and limited inland by areas of higher elevation. Made with Natural Earth.
3.4.4 Guayaquil, Ecuador

The Guayas River Estuary Ecosystem (GREE) is located in the southern province of Ecuador on the Pacific coast (2°30′–3°30′S, 79°40′–80°20′W, Figure 3.6). Alongside the Gulf of Guayaquil, it forms the largest estuarine ecosystem on the Pacific coast of South America. The estuary contains eight species of mangrove covering an area of 121,464 km² in the Guayas Province. The dominant species are Avicennia germinans and Rhizophora mangle which vary in height from <10 m to in excess of 35 m. Mean precipitation in the Guayas River drainage basin, north of Guayaquil, is 855 mm yr⁻¹ but can range from 400 to in excess of 1,800 mm yr⁻¹. The mangroves in the region are heavily influenced by the tide which is amplified to 3–5 m near the city of Guayaquil. The mangroves in the region have been heavily exploited since the 1980s with the development of shrimp mariculture in the region that provides large export revenues for Ecuador (Cifuentes et al., 1996). The mangroves occur primarily on a network of islands, connected with the mainland, divided by a series of rivers and along the coast of the estuary. The mangroves are heavily disturbed and divided by aquaculture ponds with the mangroves of the mainland encroached upon by rice paddies. At the landward margin of the mangrove is extensive agriculture on the eastern edge of the estuary whilst the western edge is dominated by large areas of bare soil interspersed with savannah vegetation. The city of Guayaquil is situated at the northern extent of the mangrove. The mangroves are able to form large homogeneous stands on the islands within the estuary whilst those along the banks of the estuary are confined to coastal fringes. The mangroves at the southern extent of the estuary are heavily disturbed by aquaculture resulting in a patchwork of fragmented mangrove forest and shrimp ponds.

Guayaquil was chosen as it represents predominantly large mangrove forests, with limited fine fringes and riverine mangroves, but which are fragmented by aquaculture. This creates artificial fringes and isolated extents within the forest that must be detected. Furthermore, the anthropogenic activity provides the opportunity to develop a method that can monitor such changes over time.
Figure 3.6: The location of the mangroves near the city of Guayaquil, Ecuador. The insert shows the mangroves [Giri et al., 2011] on the island of Isla Puna at the centre of the estuary. Made with Natural Earth.
3.4.5 French Guiana

The study site of French Guiana extends along the entire length of the coastline (5°45′–4°10′N, 53°55′–51°35′W, Figure 3.7). The mangroves of the region occupy approximately 700 ha but change rapidly in extent as they colonise newly formed sediment banks and are lost with the erosion of others. They primarily form along the coastline but also extend for several kilometres upstream on riverbanks until they are no longer under tidal influence. The mangrove is composed of four primary species; *Laguncularia racemosa, Avicennia germinans, Rhizophora mangle* and *Rhizophora racemosa* (Fromard et al., 2004, 1998). The mangroves in the region are highly dynamic with the erosion of mudbanks and the deposition of sediment delivered from the Amazon River mouth to the south, causing over 200 km$^2$ of change over the period 1951–1999 (Fromard et al., 2004). The mangrove primarily inhabits a coastal fringe and is periodically interrupted by urban settlements, including the capital city of Cayenne. A narrow section at the landward edge of the mangrove separates it from rainforest and is occupied with a mixture of savannah and rainforest vegetation, divided by agriculture, roads and urban settlements. The mangrove extents along the eastern portion of the coastline exists in larger undisturbed forests whilst the mangroves of the western portion exist almost exclusively along the coastline and are only disturbed along their landward terrestrial margin. The mangroves that extend inland along riverbanks are relatively undisturbed and blend into rainforest at their landward margins.

The French Guiana coastline provides a coastal setting with a large expanse of fringe mangrove that changes as a consequence of natural processes. The whole coastline is chosen to maximise the quantity of fringe mangrove at the study site. The large changes which have been documented at the study site provide a means of developing an accurate change detection method that operates on both annual and decadal timescales.
Figure 3.7: The coastline of French Guiana in South America. The insert (Giri et al., 2011) shows the mangroves in the region in large continuous stands along the coastline. Made with Natural Earth.
3.4.6 Venezuela/Trinidad and Tobago

This study site is composed of the coast of northwest Venezuela and the adjacent island nation of Trinidad and Tobago (Figure 3.8). The mangroves in the region are contained within 10°28’–10°50’ N and 60°54’–62°59’ W, with the majority occurring along the Venezuelan coastline. A small area of continuous mangrove is located near Port of Spain on the island of Trinidad and Tobago and has been encroached upon by agriculture and development. The Venezuelan coastline has extensive mangrove forests, forming a continuous forest along the coastline and on the fragmented islands of river estuaries. Turuepano National Park, protects the most northern mangrove forest and although the other mangroves in the region are not afforded the same protection, there is little disturbance in the region. Aside from small urban settlements, the mangroves of the region are pristine. The landward margin of the mangrove gradually turns to rainforest vegetation. To the author’s knowledge no English literature exists for the mangroves of this region.

This region is composed of relatively stable mangrove fringes that transition directly into tropical rainforest. The classifier must be capable of separating these similar land cover types, especially when their narrow extent as coastal fringes provides little training data in comparison to that offered by the much larger tropical rainforest at the study site. The small changes in extent which occur as narrow fringes and spits provide an opportunity to develop a change detection method that is sensitive to small progressive annual changes, rather than a system that is only sensitive to changes over a larger timescale (i.e. decadal).
Figure 3.8: The study location on the northern coast of eastern South America along the Venezuelan coastline and the island of Trinidad and Tobago. The mangroves of Venezuela in the insert (Giri et al., 2011) form continuous forests along the coast and along the banks of the channels. The mangrove is backed by savannah vegetation and rainforest. Made with Natural Earth.
3.5 Africa

3.5.1 Guinea Bissau

Guinea Bissau is located on the western coast of Africa (Figure 3.9) between 12°19’–10°50’N and 15°01’–16°41’W. Mangroves are abundant within Guinea Bissau which has a fragmented coastline of islands and peninsulas, dominated by species of *Rhizophora mangle*, *Laguncularia racemosa* and *Avicennia germinans* (Carreiras et al., 2012). The coastal zone is fed by four river basins along the West African Atlantic Coast, although 214,000 ha of soil is salt affected. The mean annual rainfall in the region is 1,300–2,000 mm and it has a savannah climate (Sylla et al., 1995). Guinea Bissau is one of the poorest nations in the world so development of the coastal zone has been limited with the population relying upon natural resources for subsistence due to the lack of industry (Carreiras et al., 2012). This has had a detrimental impact on mangroves in places. The mangrove stands are located in pockets along the coast of the peninsulas and do not form large continuous forests. The land cover inland from the mangrove is dominated by savannah forests.

The mangroves of Guinea Bissau were chosen as they form large networks of dendritic mangrove forests that line riverbanks in the region, which become progressively narrower inland. A monitoring system must be adept to classifying and monitoring these detailed and intricate forks, as well as the small patches of mangrove distributed amongst offshore islands, that form a disparate and fragmented environment. The mangroves in the region are stable and have undergone little change providing a region in which to monitor a pristine forest.
3.5. AFRICA

Figure 3.9: The coastline of Guinea Bissau on the western coast of northern Africa. The insert shows the mangroves in the region on the headlands, interspersed with areas of bare ground (Giri et al., 2011). Made with Natural Earth.
3.5.2 Mozambique

The mangroves of Mozambique have been studied in little detail, with most focusing on the mangroves of Maputo bay in the southern region of Mozambique, and neglecting the remaining mangroves along the coast. The mangroves of this study site lie between 17–18°N and 36–38°E, approximately 180 km northeast of the Zambezi delta (Figure 3.10). The mangroves in this region are not represented within the literature and often only overviews of the mangroves across Mozambique are provided. Species of *Avicennia* and *Rhizophora* are common in Mozambique, with additional species of *Bruguiera gymnorrhiza* and *Heritiera littoralis* common around the Zambezi delta [Semesi 1998]. The mangroves in the region occur along the mouths of rivers and occur both as continuous stands and as fragmented veins of mangrove that follow creeks within islands and along the banks of the shoreline. The mangroves have been impacted by agricultural practices although only to a limited extent, with some large forest areas being left intact. At the landward margin of the mangrove, the land cover is dominated by tropical savannah vegetation, dispersed with areas of bare soil. In wetter regions near the coast, a number of mud flats exist, on which mangroves grow in a dendritic network.

Mozambique was chosen due to its naturally fragmented mangrove forest that is directly adjacent to and transitions into riparian savannah vegetation. This provides the opportunity to assess the sensitivity of the classifier to separate adjacent forest types, especially when the fragmented small reaches of mangrove provide a limited quantity of training data. The study also shows little evidence of change to which the monitoring system must be resistant to erroneously detecting.
Figure 3.10: The study location in Mozambique on the eastern coast of Africa. The insert (Giri et al., 2011) shows the mangroves along the headlands in the region. Made with Natural Earth.
3.5.3 The Niger Delta, Nigeria

The Niger Delta is located in the south of Nigeria, originating from the river Niger, stretching 4,200 km from Guinea, through Mali and into Nigeria (Figure 3.11). The delta forms where the River Niger reaches its minimum elevation and branches into multiple distributaries. The two main rivers that feed the delta are the Niger River and the Benue River. The apex of the delta is located at Aboh (5°33′N, 6°31′E) to its southern most tip at Palm Point (4°16′N, 6°05′E). Mean monthly temperature varies between 26–27°C (James et al., 2007). Annual rainfall in the region is high (3,000–4,500 mm), peaking in July and September. The Niger delta is composed of four ecological sub-zones with mangrove being the largest and most dominant (Mmom et al., 2010). The mangroves in the region are dominated by species of *Avicennia africana*, *Rhizophora racemosa*, *Rhizophora mangle*, *Rhizophora harrisonii* and *Laguncularia racemosa*. The mangrove is also accompanied by mangrove associate species of *Nypa fruticans*, *Raphia vinifera*, *Conocarpus erectus*, *Pandanus candelabrum*, *Phoenix reclinata*, *Acrostichum aureum* and *Vossia cuspidata* (Ukpong, 1991). There is little development in the Niger Delta, with the exception of a large urban area of Port Harcourt at the eastern margin of the delta and the installation of an oil pipeline. The landward margin of the delta merges into rainforest vegetation and plantations.

The Niger Delta is an important region of mangrove in that it is one of few existing large continuous expanses of mangrove. The mangrove transitions to tropical savannah and agriculture and so accurately defining the boundary will be a requirement of the baseline classifier. There is little change in mangrove extent at the site, which will be an important factor that the change detection must accommodate by not detecting false changes. The study site is also composed of a number of mangrove species that the classifier must not be overly sensitive to.
3.5. AFRICA

Figure 3.11: The location of the Nigeria Delta on the southern coast of western Africa. The vast continuous mangrove of Giri et al. (2011) can be seen in the insert. It is interspersed with roads, pipelines and small areas of bare ground. Larger mangroves flank the creeks that fragment the islands of the delta with smaller mangroves between the creeks and channels. Made with Natural Earth.
3.6 Southeast Asia

3.6.1 Riau, Sumatra

The mangroves of Sumatra (00°–1°S and 103°–104°E) are located on the east coast within the Riau province (Figure 3.12) and have not been studied in detail. The mangroves are situated along the coastline of the mainland and a number of islands, separated from the mainland by a series of rivers, forming a delta-like estuary. The region has an 8 month long wet season with annual temperatures within the range of 23-34°C with annual average rainfall below 2,720 mm (Widyatmoko and Burgman 2006). The mangroves in the region are largely undisturbed, with little aquaculture occurring since the mid 1990’s. The mangroves form large continuous stands that fringe the coastlines of the mainland and associated islands and follow creeks and river reaches until they are no longer influenced by the tide. There are a number of small urban settlements in the region but there are also extensive oil plantations that blend into the mangrove. The potential loss of mangrove for oil plantation within the study site is unknown, with oil plantations traditionally replacing peat in the region. Despite this, an estimated 2% of palm oil plantations in the Riau region was converted from mangrove over the period 2000–2012 (Ramdani and Hino 2013), but this area was noted to be small. The mangroves in the region have increased seaward over the period 1990s–2010 with the accretion of sediment along the coast (Thomas et al. 2015).

Riau, Sumatra, was chosen as a study site as the mangroves of the region border plantation forests and tropical peatland, providing the opportunity for class confusion between land cover types. The method must be able to accurately differentiate these and classify a complex environment. Furthermore, natural mangrove advance has been documented along the coastline providing a category of change that the monitoring system must be adept to classifying.
Figure 3.12: The study site on the eastern coast of Sumatra, Indonesia. The mangroves in the region can be seen in the insert along the edges of headlands (Giri et al., 2011). Made with Natural Earth.
3.6.2 East Kalimantan, Indonesia

Two study sites are located on the Eastern coastline of Indonesia, both within the province of East Kalimantan. The study sites are sufficiently close that an overview of them is presented together (Figure 3.13). The first study site is located at the Mahakam delta while the second is located along the coastline approximately 100 km to the southwest, near the city of Tanahgrogot. The entirety of the two study sites lies between 0°00’–2°00’S and 116°00’–118°00’E. No detailed literature exists for the most southern of the two sites but the mangroves of the Mahakam delta have been previously studied. The Mahakam delta is located 50 km south of the equator and is a fan shaped delta of islands, fragmented by a series of creeks forming a deltaic estuary approximately 130,000 ha in extent. The region has a hot-tropical climate with an annual temperature range of 23–32° C. The wet season (July–September) brings precipitation of 6,700–7,000 mm per month whilst lower quantities (3,500–4,000 mm) are received during the dry season (October–June). The dominant mangrove species in the region are *Avicennia*, *Sonneratia*, *Rhizophora*, *Bruguiera*, *Xylocarpus sp.* and *Nypa sp.* (Rahman et al., 2013). Species of Nypa palm and mangrove are mixed throughout the delta with each occasionally forming continuous stands. Since the 1990s large areas of the delta have been replaced with aquaculture practices, primarily that of shrimp farming, covering 75% of the entire delta by 2010 (Rahman et al., 2013). The Mahakam delta is one of the most heavily impacted mangrove environments as a consequence of anthropogenic influence.

East Kalimantan was selected as a study site because of the heavily fragmented nature of the mangrove at the sites. This provides a two-fold opportunity. Firstly, the baseline classification method can be developed to be capable of classifying small isolated reaches of mangrove, which may be as small as the boundaries between aquaculture ponds. Secondly, the change detection method can be developed to accurately detect instances of anthropogenic change, which will provide the important information to policy makers.
Figure 3.13: The study locations in the Kalimantan region on the eastern coast of Indonesia. The mangrove in the region as defined by Giri et al. (2011) is heavily fragmented by the extensive aquaculture in the region on the islands of the delta. Made with Natural Earth.
3.6.3 Perak, Malaysia

The Matang Forest Reserve (4°00′–5°00′N and 100°00′–101°00′E) is situated in the state of Perak on the northwest coast of peninsular Malaysia (Figure 3.14). The reserve stretches for approximately 50 km along the coast of Malacca. The forest reserve occupies continuous forest along the coastline of the mainland and a number of islands segregated from the mainland by a network of narrow rivers. The reserve is covered by approximately 42,000 ha of mangrove and is a managed mangrove forest, primarily for the production of *Rhizophora apiculata* for charcoal on a 30-year rotation cycle (Gan, 1995; Sasekumar and Chong, 1998; Alongi et al., 1998). The annual precipitation over the forest is 3,990 mm. The tidal range is 2 m and does not drain the channels around the island at low tide. The mangrove forest is divided between mature and managed species, with the former composed of a mixture of mangrove species dominated by *Rhizophora apiculata* whilst the managed forest is dominated by *R. apiculata Blume*. Other common species include *Bruguiera gymnorrhiza* and *B. parviflora* (Putz and Chan, 1986). The forest is well preserved, apart from what is removed for charcoal production but is generally hailed as a good example of a well managed and well preserved forest. The islands are particularly well preserved whilst the mainland forests have been encroached upon to some degree by urban areas, agriculture and plantations, although this is at the landward margin of the forest with the interior remaining undisturbed.

Perak is chosen as a study site because of the logging rotation cycles that are used to harvest the mangrove. This provides an opportunity to develop the method to omit the logged areas although they are surrounded by large mangrove stands and contain degraded mangrove vegetation. The logged areas are also left to regrow, providing a system to be developed that is able to accurately monitor the cycle of mangrove growth and removal that would be critical for providing the most accurate maps of forest extent.
Figure 3.14: The study site on the western coast of Malaysia with the mangrove growing in the Matang forest reserve. Within the forest the variation in the mangrove reflects the rotation cycles of mangrove harvested for charcoal production (Giri et al., 2011). Made with Natural Earth.
3.7 Oceania

3.7.1 Kakadu National Park, Australia

The mangroves of Kakadu National Park are situated in Northern Territory, Australia (12°00’–13°00’S and 132°00’–133°00’E), 150 km East of Darwin (Figure 3.15). The mangroves are within a national park and occur in narrow fringes along the banks of the Wildman River, West Alligator River, East Alligator River, South Alligator River and on Barron Islands. The source of these rivers is provided by the Arnhem plateau that descends in escarpments inland (Mitchell et al., 2007). Freshwater wetlands dominate the area within 30 km of the coast (Finlayson and Woodroffe, 1996) with the environment turning to tropical savannah south of this and eventually into desert as the interior of the continent is approached. The region experiences a tropical monsoonal climate, composed of a wet (November-March) and dry (May-September) season (McQuade et al., 1996). Annual average precipitation in the region is 1,483 mm with mean minimum and maximum annual temperatures of 21°C and 33°C, respectively (Bureau of Meteorology, 1999). A typical transect through mangroves in the region would comprise *Sonneratia alba* along the seaward extent, fringing an area of *Rhizophora stylosa* with a landward leading edge of *Avicennia marina* (Davie, 1984). The mangroves follow this distinct zonation pattern due to the varying tolerances of different species to the coastal environmental characteristics, such as salinity, wave action and sedimentation (Finlayson and Woodroffe, 1996; Bayliss et al., 1997). The mangrove primarily occur along the banks of the mouths of the rivers at the coast but are able to extend inland along the river banks that dissect a large area of mudflat. The region is undisturbed by anthropogenic activity.

The mangroves of Kakadu occur in fine narrow coastal fringes that are susceptible to the influence of the sea. It is important that the method can accurately classify limited extents of forest and monitor subtle changes. This extent, whilst small at the global level, is regionally important. An update to the global extent must include mangrove forests such as these.
Figure 3.15: The location of the mangroves in northern Australia. The mangroves within the Kakadu National Park are confined to three rivers in the region and in narrow fringes along the coastline, as mapped by Giri et al. (2011). An example of the mangroves in the West Alligator River is available in the insert. Made with Natural Earth.
Chapter 4

Datasets and Pre-processing

This chapter outlines the datasets used in this study and their pre-processing. The chapter will conclude by detailing the software tools used in this work.

4.1 Background

Remotely sensed data is available in the form of in-situ, airborne and satellite data which are able to provide a range of imaging and non-imaging datatypes. This work will focus upon the imagery acquired from satellites. Satellite data is most suited for this work, as to develop a mangrove mapping and monitoring system applicable to mangrove forests across the world, the availability of data over large areas is required. Satellite data is available in a variety of modes with full global coverage of optical and radar datasets attainable. Each mode of data has benefits and limitations for mangrove mapping.

Optical data is suited for retrieving the biophysical characteristics of a land cover type, namely the productivity and moisture of the vegetation, which are useful characteristics for the mapping of wetland vegetation. Variations in the surface reflectance values, measured by the sensor, can be used to distinguish land cover types from one another based upon their characteristics (Lillesand et al., 2014). A limitation of optical data is that spectral reflectance cannot be used as a measure of the structural properties of the land cover, such as the structure of a tree.
4.1. BACKGROUND

canopy or trunk size. In addition, the acquisition of cloud-free data, especially in the tropics, is difficult to achieve.

Radar data is also available via satellite acquisition and is able to overcome some of the limitations of optical imagery. Although radar data is not capable of retrieving the biochemical properties of land cover types, they are able to acquire data pertaining to their structural properties. The microwave wavelengths of radar sensors are much larger than that of their optical counterparts and are sensitive to the physical characteristics of the target, such as their size, shape and orientation. These microwaves are sensitive to the moisture content and electrical conductivity of the target (Woodhouse, 2005). The larger microwave wavelength provides the additional benefit of reduced attenuation by the atmosphere and as such are able to acquire images of the Earth’s surface irrespective of cloud cover.

Optical and radar data are available across the globe at comparable medium resolutions of 20–30 m and can be used in combination to the greater benefit of using one dataset alone (Fatoyinbo and Simard, 2013). Furthermore, to develop a monitoring system requires the continued availability of a dataset into the future. Optical and radar sensors are expected to continue with the growing interest in the field of Earth observation. Optical data is expected to be continually available in the future with the continuation of the Landsat and European Space agency (ESA) missions whilst radar data will be provided by Japanese Aerospace Exploration Agency (JAXA) and ESA missions, also.

Additional datasets, derived from remotely sensed data are able to acquire additional information beyond that of satellite imagery. Digital Elevation Models (DEMs) are particularly useful datasets within remote sensing as they provide 3 dimensional information (i.e. elevation) on the environment. Elevation data can be acquired via numerous methods yet common remotely sensed methods include lidar and radar interferometry. Little lidar data is available consistently across the globe, yet a number of elevation datasets derived from radar data are available. One of these, the Shuttle Radar Topography Mission (SRTM) Digital
Surface Model (DSM), is freely available across the majority of the globe, with the exception of very high latitudes. In addition to this, ancillary data derived from satellite products can provide important knowledge to aid in the accurate processing of data. This may include existing maps of the area of interest or may be used to mask out undesirable regions of an image. The greater the number and types of datasets available, the greater the user of the data is equipped to achieve their objectives.

The following sections provide a detailed overview of the datasets used in this work and the steps taken during the pre-processing of this data, ready for use within the study.

### 4.2 ALOS PALSAR/JERS-1 radar imagery

The Advanced Land Observing Satellite (ALOS) was the flagship platform of the Japanese Aerospace Exploration Agency (JAXA) and was launched from JAXA’s Tangashima Space Centre on January 24th 2006 aboard a H-IIA rocket. The satellite is in a sun synchronous orbit at an altitude of 691.65 km. The recurrence cycle of the platform is 46 days and requires 671 passes to attain complete global coverage. The platform is powered by an expandable solar array paddle which measures 3 m by 22 m, composed of 9 segments. ALOS carries three sensors, the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) at a resolution of 2.5 m, the Advanced Visible and Near-Infrared Radiometer (AVNIR-2) at a resolution of 10 m and the Phased Array L-band Synthetic Aperture Radar (PALSAR) sensor, available at a variety of resolutions. The PALSAR sensor is a fully polarimetric radar sensor and is an enhanced version of its predecessor aboard JERS-1. The sensor operates in L-band with a 1,270 MHz (23.6 cm) centre frequency and 14 and 28 MHz bandwidths. The observation was initiated in 2006 and has resulted in a homogeneous archive of data for the globe, providing time-series data previously only available for products at a coarser resolution [Rosenqvist et al. 2007]. Communication with ALOS was lost in 2010 and the sensor was subsequently decommissioned.
4.2. ALOS PALSAR/JERS-1 RADAR IMAGERY

In addition to imagery gathered by ALOS PALSAR, this study used additional radar imagery gathered by the Japanese Earth Resource Satellite (JERS-1). JERS-1 was launched by JAXA (then NASDA) during Feb 1992, carrying an L-band SAR sensor at HH polarization. The satellite repeat cycle was 44 days, using an image swath width of 75 km. JERS-1 utilised a unique orbital pattern, designed so that adjacent passes were acquired on consecutive days. This enabled JERS-1 to acquire temporally homogeneous data over large areas through just a 1 day time difference between neighbouring passes. JERS-1 was operational for 6.5 years, with the mission ending in October 1998 (Rosenqvist et al., 2004).

4.2.1 Radar characteristics for mangrove mapping

Radar systems are those that propagate electromagnetic energy of specific wavelengths towards a target and measure the reflected energy back at the receiver, ultimately providing a measure of the distance of a target from the sensor. The resolution of a radar system is divided into that of the range (across track) and azimuth (along track) resolutions. The range resolution is defined by the pulse length and the along track resolution is defined by the size of the antenna in proportion to its distance from the target. For a real-aperture system higher resolutions are obtained through the use of a larger antenna which is a limiting factor for spaceborne systems that are at a great distance from the target. To overcome this, synthetic aperture radar (SAR) uses the movement of the platform along the along-track to synthesise a large antenna and attain higher azimuth resolutions (Henderson and Lewis, 1998).

The detection of the target is dependent upon a number of variables, dependent upon the settings of the sensors, the characteristics of microwave energy and the properties of the target. For a detailed description of the principles of radar and SAR, see Woodhouse (2005).

Radar data provides a number of distinct advantages over that of the use of optical datasets. The greatest benefit of radar data is the ability of its wavelengths to penetrate the atmosphere such that it is not inhibited by cloud cover. The
wavelengths of microwave energy are much larger than that of optical wavelengths and the particulates in the atmosphere that scatter them. As a consequence of this, the atmosphere does not inhibit the transmission of microwave energy. Furthermore radar is an active system and which can acquire imagery independently of solar illumination. These properties are particularly useful for developing a monitoring system as data can be regularly acquired with a dense temporal resolution.

Radar data is sensitive to the structural components of vegetation and is therefore able to distinguish between land cover and vegetation types that may have similar spectral yet different structural properties. The orientation of the electric plane of the wave defines its polarisation. Waves that are aligned with the \(x\)-axis are horizontally polarized and those that are aligned along the \(y\)-axis are vertically polarised (Woodhouse, 2005). The transmission and reception of these form either co-polarised (HH, VV) or cross-polarised (HV, VH) images. The importance of this for the remote sensing of mangrove forests is that the interaction between the radar and the mangrove differs with variations in the wave polarisation. A high response in horizontally transmitted and horizontally received energy (HH) is indicative that the interaction of the incident energy was with a vertical structure, such as a mangrove trunk. Conversely, receiving vertically polarised energy would indicate that the incident energy has interacted with a structure that has caused the polarisation of the wave to change, such as a mangrove canopy (Lucas et al., 2007). Furthermore, these larger wavelengths are able to provide information on the structure of the vegetation as some are able to penetrate the canopy of the forest. Higher frequency, shorter wavelength radar has been observed to interact with the canopy components of mangrove forests, such as the leaves and twigs of the canopy. L-band radar used in this work is a lower frequency radar and is capable of penetrating the mangrove forest canopy and interacting with the larger woody components of the mangrove forest. At lower values of biomass this interaction occurs with the trunk of the mangrove and sufficiently large components of the canopy (Mougin et al., 1999; Proisy et al., 2000, 2002; Wang et al., 1995).
4.2.2 Radar pre-processing

The images were provided from JAXA in compressed format. The data were extracted for each scene and an accompanying JAXA formatted header file was parsed and restructured into an ENVI readable format using Python. The image format was converted into KEA to minimize the file size whilst maintaining image quality and projection information. Some regions of interest were located at the intersection of 2 or more radar images and were mosaicked into a single region.

SAR imagery inherently contains speckle which is a product of the combination of the backscatter of objects illuminated by the incident radar pulse. Each object that is illuminated by the radar will interact differently with the incident pulse and return backscatter towards the sensor. The sensor then coherently sums the backscatter for all illuminated objects. Depending upon whether the coherence causes constructive or destructive interference this affects the brightness of the portion of the image (pixel). The consequence of this is a radar image with a grainy texture as pixels vary in brightness (Henderson and Lewis, 1998). In order to remove such speckle, the image was smoothed, using a Lee filter (Lee, 1980) which is able to suppress radar image speckle whilst maintaining image detail, using a window $3 \times 3$ window size. All of the radar data was processed in this manner.

Radar backscatter is measured in power but these values are small yet occur over a large range. To avoid using image values such as this, the data can be converted to a log scale, decibels (dB).

The expression to convert ALOS PALSAR/JERS-1 digital number (DN) data to dB is the same for both sensors, with only a difference in the calibration factor value (CF) required:

$$10 \times \text{LOG(DN}^2) + \text{CF}$$

The CF for JERS-1 data is -84.66 and for ALOS PALSAR data is -83.
A 2010 ALOS PALSAR colour composite (R:HH, G:HV, B:HH/HV) image and a 1996 JERS-1 (HH) image are provided in 4.1.

Figure 4.1: Radar imagery at Guayaquil, Ecuador. A) ALOS PALSAR RGB R: HH, G:HV, B:HH/HV. B) JERS-1 HH image band.

4.3 Landsat composite imagery

The radar data was supplemented with an optical dataset. The optical dataset was a global cloud free composite mosaic of Landsat 7 (ETM+) data generated by Hansen et al. (2013) and used in the generation of a global forest map for the year 2013. Where cloud-free data was not available the most recent cloud free scene was acquired, over the range 2010–2013. The global composite is composed of over 650,000 Landsat scenes, comprising 143 billion 30 m Landsat pixels. Only growing season Landsat scenes were considered for the mosaic due to the benefits this afforded the mapping of global forest cover over imagery captured during the senescent/dormant seasons. Each scene was resampled, converted to Top of Atmosphere reflectance (TOA), cloud, water and shadow masked and normalised.
4.3. **LANDSAT COMPOSITE IMAGERY**

This process was tested on national scale composites across the globe. The data is provided in four spectral bands; Red (band 3), Near Infrared (NIR:band 4), Short Wave Infrared 1 (SWIR:band 5) and Short Wave Infrared 2 (SWIR:band 7). The primary limitation of the dataset is that the image is a composite composed of multiple dates and scenes and therefore, a land cover class may not have a consistent reflectance across its extent. However, this can be overcome with the use of normalized indices, such as the Normalized Difference Vegetation Index (NDVI). This limitation, however, is outweighed by the advantages that the dataset can provide. The dataset of [Hansen et al. (2013)](http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html) was processed using the Google Earth Engine cloud processor and all scenes are available to download from: http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html.

The data was subsetted, resampled and reprojected to that of the radar imagery. This was achieved using a combination of RSGISLib and GDAL. Vegetation indices were derived from this scene including the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Waterband Index (NDWI), using the expression (NIR-RED)/(NIR+RED) and (NIR-SWIR)/(NIR+SWIR), respectively. These indices were chosen as they provide information on the photosynthetic productivity and water content of vegetated land cover types, respectively. The number of vegetation indices that could be derived were limited by the spectral range of the global mosaic which was composed of 4 spectral bands.

A subset of the [Hansen et al. (2013)](http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html) Landsat mosaic is provided in Figure 4.2 using the image band sequence R:NIR, G:SWIR, B:Red.

### 4.3.0.1 Landsat 5 imagery

A number of Landsat composite images could not be used due to insufficient quality of the scenes. This was caused by excessive striping in the scenes due to the effect of mosaicking multiple Landsat scenes. In addition, the composite scenes are watermasked, causing the boundaries between the land and water to become degraded in places. The mangrove of Kakadu National Park occur in narrow fringes at the interface between land and sea and within smaller river channels.
Figure 4.2: The Hansen et al. (2013) composite mosaic over the Bragantina coast, Brazil.
4.3. LANDSAT COMPOSITE IMAGERY

and were degraded by the watermask. Similarly, as the composite imagery is composed of time-series images, areas of mangrove logging were observed to be a patchwork of logged mangroves and regrowth due to the temporal difference in the scenes used in the mosaic. This was observed at Perak, Malaysia, where the forest is logged in blocks as part of a rotation cycle for the harvest of charcoal (Gan, 1995). A comparison of the Hansen et al. (2013) Landsat composite mosaic with a Landsat 5 TM scene is provided in Figure 4.3.

In these instances where the Landsat composite imagery was observed to be insufficient, a Landsat scene was used instead. Landsat 5 TM imagery was used to avoid the scan line error of Landsat 7 ETM+ and to ensure that a scene could be acquired as close to the baseline date (2010) as possible. A Landsat scene was acquired from the USGS Earth Explorer archive for both Kakadu and Perak, with as little cloud in the imagery as possible. A little cloud was evident in the Perak imagery but it did not cover the mangrove forests whilst the Kakadu scene was almost completely cloud free. Landsat scenes are larger in extent that ALOS scenes and one was sufficient to cover the region of interest at both locations. The imagery was cloud masked and corrected to top of atmosphere (TOA) using the open source Atmospheric and Radiometric Calibration of Satellite Imagery (ARCSI) Software (Bunting and Lucas, 2014). The data was subsequently subset to the extent of the ALOS scenes and was simultaneously reprojected to the local UTM projection. The NDVI and NDWI were calculated from the imagery, as with the Landsat composite imagery.
CHAPTER 4. DATASETS AND PRE-PROCESSING

Figure 4.3: A comparison between the Hansen et al. (2013) Landsat composite and a Landsat 5 TM scene at Perak, Malaysia. Left: The composite is of poor quality and the areas of logging within the forest are not clearly defined. Right: The image quality is higher and the mangrove extent is more accurately defined.
4.4 Elevation: Digital Surface Model (DSM)

Elevation data was provided in the form of the Shuttle Radar Topography Mission (SRTM) DSM. The SRTM is a DEM generated seamlessly across the globe for the regions between 60°N and 54°S. The SRTM was generated using interferometric SAR, using equipment aboard the Space Shuttle Endeavour on Flight STS-99 launched on February 11th, 1999. In order to generate an interferometric image, the space shuttle contained an expandable 60 m long 13 ton mast. The SRTM was generated using two microwave wavelengths (C and X) although only the C band SRT was utilised in this study. The DEM was generated from 159 orbits using a swath width of 225 km. The SRTM was originally made available at 30 m across the US and 90 m across the remainder of the tropics (Van Zyl, 2001), although since this work was initiated a 30 m product for the globe has been released. Although the SRTM DSM is a decade older than the most recent radar scene and is at 90 m resolution, the dataset was used to exclude regions of high altitude where mangroves do not occur and was not used to accurately infer vegetation height. The SRTM dataset was acquired from the USGS. It was subset, resampled and reprojected as required using a combination of RSGISLib and GDAL to the extent of the input radar scene in the same manner as the optical mosaic.

4.5 Existing mangrove extent maps

An existing mangrove baseline was incorporated into the method in order to attain statistics regarding the characteristics of mangrove forests and to gather training to input into the classification algorithm. The existing mangrove baseline was generated using a combination of existing global mangrove maps.

The map of Giri et al. (2011) was generated using Earth observation data, primarily the Global Land Survey (GLS) and Landsat archive. Using training samples, hybrid supervised and unsupervised image classification algorithms were conducted on approximately 1000 Landsat images. This produced an update to the previously existing mangrove baseline to the year 2000 (Giri et al., 2011). A second map built upon the work of Giri et al. (2011) and corrected inaccuracies
in the data and included data from missing regions using remotely sensed data (Giri et al., 2011). A third map was that of Spalding et al. (1997). This map built upon data compiled in a GIS by the World Conservation Monitoring Centre (WCMC) to form ‘The Conservation Atlas of Tropical Forest’, from a range of data from detailed digital datasets to field sketch maps. This was updated in 2010 by the WCMC to form a fourth map (Spalding, 2010) which classified remotely sensed data, primarily for areas of poor quality or insufficient data using an unsupervised classification algorithm.

4.5.1 Generation of the training dataset mask

The map of Giri et al. (2011) was acquired in raster format whilst the other datasets were acquired from the WCMC online Ocean Data viewer as shapefiles. The extents of the study site regions were subset to those of the radar imagery using a combination of RSGISLib and GDAL. The vector datasets were subsequently rasterised to the resolution of the ALOS PALSAR imagery (25 m). All raster datasets were added together to form a single mangrove extent with values in 1–4 and this dataset was subsequently duplicated as a separate binary image. Using RSGISLib the binary image was clumped so that continuous pixels of mangrove extent in the images were aggregated into objects. The area of each clump could then be readily retrieved and small clumps (<1 ha) were removed, thus removing noise from the imagery. The clumped image was intersect with the original combined raster, with values in 1–4. A $5 \times 5$ median filter was then applied to the output and bandmath was used within RSGISLib to create a single image with values ranging from 1–2, with each pixel defined by the combined occurrence of the mangrove extent datasets. These steps are represented in Figure 4.4 and an example of the a priori layer is provided in Figure 4.5. The Spalding et al. (1997) layer was removed from the process as its extent was observed to be too inaccurate for use.
4.6 Free and Open Source Software (FOSS)

Free and Open Source Software has become increasingly emergent in geospatial analysis and now includes a sufficient quantity of libraries to rival the use of traditionally expensive software designed for processing remote sensing and GIS data (e.g. ESRI’s ArcMap). The primary benefit of open source software is its free acquisition, but more importantly for this work is its increased scalability over traditional proprietary software. This is an increasingly important benefit as vast quantities of processing power are increasingly available with the growing popularity and access to high performance computers (Clewley et al., 2014), enabling studies to be carried out over large geographical areas.

This study utilised an object oriented approach and thus required a suite of software capable of image segmentation and classifying the subsequent image objects. Furthermore, this required a file format that could support such requirements whilst storing large quantities of data efficiently. Finally, software was required to view the images and results as part of the development of the method.
Figure 4.5: An example of the *a priori* dataset at Riau, Sumatra. A higher weighting is assigned where multiple mangrove extents overlap.
4.6.1 Python

Python is an open source scripting language available online[1]. Python is a scripting language which boasts two major benefits for use in geospatial analysis. Firstly, Python is ‘general-purpose’ in that it is not designed to work within a single domain or for a single specific application but can be applied to a range of purposes. Secondly, Python is a ‘high-level’ scripting language in that it is not designed to do the work of a machine language and is instead focused on optimising readability rather than program efficiency. The greatest use of the language within this study was in the construction of processing chains, from pre-processing through to analysis of the results.

4.6.2 RSGISLib

The Remote Sensing and GIS Library (RSGISLib) is a suite of tools for processing remote sensing and GIS software [Bunting et al., 2014]. The library currently contains over 300 algorithms for processing data, including modules for image calibration, image classification, image calculation, image filtering, image registration, vector processing and zonal statistics. RSGISLib is available through a series of python modules. The majority of the geospatial analysis within this study was carried out using RSGISLib. As RSGISLib can be used within Python, it is scalable and can be used on small or very large datasets, using single commands on a desktop computer processor through to high-performance multi-core processing on a HPC. RSGISLib is available to download from the software website[2].

4.6.3 GDAL

The Geospatial Data Abstraction Library (GDAL) is a software package designed to translate between image formats commonly found within the field of geospatial analysis, including raster and vector formats provided by open source and proprietary software. In addition to this, GDAL also provides a limited number of command line algorithms for processing data, such as mosaicking, reprojecting,

[1] https://www.python.org/
and converting between raster and vector dataset formats. GDAL provides a Python interface and can be readily incorporated into processing chains within a Python script. The primary use of GDAL within this study was for the preprocessing of the remotely sensed data and for accessing images, such as the object values of the segmented imagery. GDAL is available to download online\(^3\).

### 4.6.4 RIOS

Raster I/O Simplification (RIOS) is a set of python modules built upon GDAL to relieve the user from the task of opening and closing files, checking projection information, image alignment and writing image header files, enabling the user to focus on processing the data within the image. RIOS also provides a memory efficient method of processing large quantities of data by accessing the image as a NumPy array and stepping through the image in small blocks at a time. RIOS was used to process large datasets in a memory efficient manner. This was especially useful when large image mosaics with multiple bands were processed. RIOS is hosted on the code repository Bitbucket\(^4\).

### 4.6.5 KEA Image Format

Despite the plethora of image file formats within the field of geospatial analysis, no single file type is able to simultaneously support lossless compression, large file sizes, ground control points, raster attribute tables and inbuilt image pyramids. To remedy this, the KEA file format was designed to contain all of these attributes whilst being fully GDAL compatible (Bunting and Gillingham, 2013). These attributes enable the file format to support a large Raster Attribute Table (RAT) which is fundamental to achieving an object oriented classification. The KEA file format can be used in any software that implements a GDAL driver, provided the KEA library is installed. The KEA library is available at the developers website\(^5\).

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\(^3\) http://www.gdal.org
\(^4\) https://bitbucket.org/chchrsc/rios
\(^5\) https://kealib.org
4.6.6 TuiView

Traditionally, remotely sensed imagery would have to be viewed in proprietary software, such as ESRI’s ArcMap or Excelis’ ENVI software. Whilst this was adequate for viewing a number of discrete scenes, these software packages were limited in their ability to quickly and efficiently display large files and perform simple queries. TuiView is a simple image viewer written in Python, designed with the purpose of quickly viewing and querying imagery which may be large in size in an efficient manner. TuiView is available on the software website 6.

4.6.7 Atmospheric and Radiometric Calibration of Satellite Imagery (ARCSI)

ARCSI is a command line interface tool for the atmospheric correction and radiometric calibration of optical satellite imagery. ARCSI is used to generate the necessary parameters to implement the 6S atmospheric correction software algorithms in an as automated fashion as possible. ARCSI can be used to correct a suite of optical imagery including all of the available Landsat, RapidEye and Worldview sensors, amongst others (Bunting and Lucas 2014). ARCSI is free and open source software and is available to download via RSGISLib[7].

6 https://tuiview.org
7 https://rsgislib.org/arcsi
Chapter 5

Drivers and distribution of changes in mangrove extent

This chapter investigates the distribution of drivers that cause changes in mangrove forest extent across the tropics. The chapter uses time-series colour composite imagery to achieve this and provides estimates of the global proportion of mangrove that is potentially at risk.

5.1 Background

Chapter 1 outlined the loss of mangrove forests across the globe as a consequence of anthropogenic activity, natural processes and climate change. Although this change and its drivers have been well documented, the distribution and frequency of these drivers of change have not been mapped by a single study. Whilst the drivers of change in mangrove forest extent have been observed over time at individual study locations, this has not been achieved at a global level. This is despite the knowledge that mangrove forests have been degraded across their range within the last century (Valiela et al., 2001) and may become functionally extinct by the turn of the next century (Duke et al., 2007).

Remote sensing provides a means of being able to observe a phenomenon through time, with the use of time-series imagery. This chapter utilised time-series radar
imagery acquired over a 14 year period for detecting the causes of change in mangrove forest extent (Thomas et al., 2015). Japanese radar data have been acquired systematically across the globe and such data have been made increasingly available free of charge. The ALOS PALSAR sensor operated in 2006–2010 providing a short period over which time-series imagery was acquired but this is supplemented with additional JERS-1 imagery that was captured during the 1990s. This broadens the temporal archive of radar imagery to two decades which is useful for monitoring large scale changes to phenomena that can occur over short periods of time. Time-series radar is suited to monitoring change in the tropics as cloud free imagery can be consistently acquired, enabling land cover types to be continually monitored.

Time-series analysis can utilise computer vision algorithms to recognise features and detect changes in them, but can also be used for manually assessing the changes in land cover. Variations in radar backscatter over time, in response to changes in the biophysical structural properties of the target being imaged, enables changes to land cover types to be readily identified by an interpreter. Time-series colour composite images provide a means of inferring changes in land cover types through the varying response in the bands that populate the composite image, subsequently enabling the qualitative assessment of changes in land cover. The manual interrogation of such data yields changes in real-world objects recognised by the interpreter (i.e. a forest) rather than objects identified by computer vision algorithms. Although this is more subjective as no pixel values are quantified, the development of computer vision algorithms to do this are beyond the scope of this work. An interpreter is also able to benefit from being able to infer the context of an object within its environment and recognise specific land cover types and changes of interest. Radar imagery can be used for this over the tropics as it is uninhibited by cloud cover so that changes that have occurred to a specific land cover type can be detected.
5.2 Method

Time-series colour composite images were generated by stacking imagery to form one RGB image. The colour composite image was composed of a JERS-1 radar scene and two ALOS PALSAR scenes. The earliest (1996) JERS-1 scene was loaded into the red channel, a 2007 PALSAR scene was loaded into the green channel and the most recent (2010) PALSAR scene was loaded into the blue channel. As each band of the RGB image is associated with a particular date, changes in time can be inferred from the colours visible in the imagery.

Through the JAXA K&C initiative, time-series of 1996 JERS-1 imagery (HH) and 2007 and 2010 ALOS PALSAR imagery (HH) data were compiled to generate colour composite tiles measuring 1° × 1° in extent at 25 m pixel resolution. The tiles were provided in KML format for viewing within Google Earth software. The total extent of the colour composite dataset was defined using the mangrove map of Giri et al. (2011). The tiles were imported into Google Earth for the visual analysis of change, visible as colours in the RGB composite images. The total number of tiles analysed was 1172, which were chosen from a larger dataset where poor or missing data rendered some scenes unusable. This data was concentrated along the coastal zone of China and accounted for 3.5% of the total data. The dataset was divided into regions, namely North and Central America (including the Caribbean), South America, Africa, Middle East & India (MEI), Southeast Asia and Oceania (Australia, New Zealand and Pacific Islands). Each region was then manually interrogated for evidence of change in mangrove extent.

A decrease in backscatter from 1996, synonymous with the removal of mangroves, was observed in the image as a distinct red region due to the high backscatter values relative to 2007 and 2010. Conversely, distinct blue regions were observed as a consequence of an increase in backscatter by 2010, synonymous with the colonisation of a section of coastline by mangroves. This was common along shorelines where mangrove colonisation increased the backscatter as a consequence of the change from a smooth water surface to a rough mangrove environment. Dis-
tinct regions of green in the imagery were synonymous with the colonisation and subsequent loss or degradation of mangroves over the 14-year period (1996-2010) with increases and subsequent decreases in backscatter. Cyan (2007,2010), magenta (1996,2010) and yellow (1996,2007) were synonymous with degrees of change within this period (Table 5.1). The colouration was used in combination with the shape of the potential change feature and its context within the environment, such as its location within, or proximity to, the mangrove forest. This required the subjectivity of the interpreter in combination with the knowledge that natural changes do not form geometric boundaries and shapes, as with anthropogenically driven changes. Irregularly shaped changes on the seaward margin of existing mangrove forests were interpreted as a gain or loss of mangrove extent. Similarly, geometric shapes with specific colouration within the forest were interpreted as being anthropogenically driven change. It is acknowledged that similar backscatter to mangrove forests could also be caused by other land cover types (e.g. urban) within the mangrove forest. In these such instances other properties such as shape and context are used to identify a possible misinterpretation and the feature can be checked in the underlying Google imagery. Causes of change were therefore recognised using a combination of colour and physical descriptors.

The categories of change identified were, Intact, Prior Disturbance, Erosion, Deposition/Regrowth, Aquaculture/Agriculture, Dieback and Logging. Examples of these processes are shown in Figure 5.1. Each channel of the composite represented a specific point in time and the composite therefore provided a means of inferring change to the mangrove extent through time (Figure 5.2). Each category was identified using the following criteria.

**Intact** Intact mangrove is recognised by a coastal forest extent that is grey/white in colour and shows no evidence of natural or anthropogenic change.

**Prior disturbance** Prior disturbance shows no bright but forms an unnatural boundary next to or within the mangrove forest. Aquaculture is a common example of this as the ponds form black geometric shapes within the
Mangrove. 

**Mangrove Loss (erosion)** This is identified using a combination of a deep red colouring and its context within the scene. Its commonly forms on the seaward margin of the mangrove and has an irregular shape.

**Mangrove gain (deposition/regrowth)** This has a distinct blue/green colouring and forms on the seaward margin of the mangrove extent with an irregular boundary.

**Aquaculture/Agriculture** This degradation is evident as geometric shapes that have a boundary with or within the mangrove. Aquaculture shows a distinct red colouring while agriculture is multicoloured due to crop cycles and has lines associated with roads in between crops.

**Mangrove dieback** Mangrove dieback shows no geometric shape but has a red/pink colouring associated with a decrease in backscatter with a loss of biomass. This colouring occurs in a forest that otherwise looks intact.

**Logging** Logging forms a patchwork of geometric shapes within the mangrove with either a red, green or blue colouring associated with areas of logging and regrowth.

An accuracy assessment was carried out by comparing changes observed in the radar dataset with moderate (30 m) resolution Landsat dense time-series available, via the Google Earth Engine, from 1984 through to 2012 following Thomas et al. (2015). Due to the comparable resolution of Landsat (30 m) with ALOS PALSAR (25 m) imagery, the Landsat dense time-series can be used efficiently to validate observed changes through time. A sample of 30 occurrences of change from each change-class were selected at random, with a total sample of 159 occurrences of change being validated. In instances where less than 30 occurrences were observed, the maximum number of occurrences for each class was validated. The observed change in the tile was then sought in the dense time-series imagery.

Although these results provide information on the global distribution of the causes of changes in mangrove forest extent, it assumed that mangrove forests were
globally evenly distributed. It is not known, therefore, whether the changes identified are occurring within large areas of mangroves or along fine fringes. This is important because aquaculture identified within a tile with a large mangrove extent places a large quantity of mangrove within an ‘at risk’ region. There was no indication, therefore, of how the drivers of change were geographically distributed in relation to the global distribution of mangrove. To address this, the mangrove map of Giri et al. (2011) was used to quantify the mangrove area contained within each $1\degree \times 1\degree$ tile. This provided an indication as to whether the changes observed were affecting regions with small or large quantities of mangrove. The knowledge as to whether the greatest occurrences of change were located in regions with the greatest areas of mangrove, indicated as to whether large areas of mangrove were at risk of changes, outside of those that occurred naturally (i.e. anthropogenic activity). The results are presented as percentages of the total mangrove area calculated from the total mangrove pixels within each tile.

Figure 5.1: Examples of the categories of change identified within the colour composite imagery. Changes in mangrove extent were identified through a combination of their colour in the composite imagery, their shape and the context of the surrounding environment. Examples of the categories of change are a) Intact mangroves in Papua. b) Prior disturbance (aquaculture) at Guayaquil, Ecuador. c) Loss of mangrove along the coastline of French Guiana. d) Colonisation of mangrove along the French Guiana coastline. e) Extensive aquaculture at the Mahakam Delta, Kalimantan, Borneo. f) Mangrove dieback in West Papua. g) Logging within the managed Matang forest reserve, Perak, Malaysia. h) Prior and on-going agriculture in Sumatra.
Figure 5.2: A time-series composite image enables the interpretation of changes to land cover through time. The radar imagery was loaded into the following image bands, as displayed in b): Red: 1996 JERS-1 (HH), Green: 2007 PALSAR (HH), Blue: 2010 PALSAR (HH). A high backscatter in 1996 and low backscatter in 2007 and 2010 gave a distinctive red colour, synonymous with mangrove loss (aiii). Opposite to this, mangrove advance was blue (ai) as backscatter was increased in 2010 over 2007 and 1996. Mangrove advance and subsequent loss between 1996 and 2010 was evident through a distinct green colour (aii) as the feature occurred in the 2007 radar image alone.
Table 5.1: Dates of change in mangrove extent inferred from the colour composite time-series imagery. Each band of the colour composite is of a specific year, enabling changes in mangrove extent to be inferred from the colours in the image.

<table>
<thead>
<tr>
<th>Colour</th>
<th>Cause</th>
<th>Process</th>
<th>change</th>
<th>Inferred</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>High backscatter in red band (1990s radar)</td>
<td>Mangrove present</td>
<td>1990s-2007 only</td>
<td>Removal of mangrove post 1990s</td>
</tr>
<tr>
<td>Green</td>
<td>High backscatter in green band (2007 radar)</td>
<td>Mangrove present</td>
<td>in 2007 only</td>
<td>Mangrove growth between 1990s-2007, retreat by 2010</td>
</tr>
<tr>
<td>Blue</td>
<td>High backscatter in blue band (2010 radar)</td>
<td>Mangrove present</td>
<td>in 2010 only</td>
<td>Mangrove advance from 2010</td>
</tr>
<tr>
<td>Magenta</td>
<td>High backscatter in red and blue bands (1990s/2010 radar)</td>
<td>Mangrove present in</td>
<td>1990s and 2010 imagery</td>
<td>Removal of mangrove and regrowth between 1990s-2010</td>
</tr>
<tr>
<td>Yellow</td>
<td>High backscatter in red and green bands (1990s/2007 radar)</td>
<td>Mangrove present in</td>
<td>1990s and 2007 imagery</td>
<td>Mangrove retreat from 2007</td>
</tr>
</tbody>
</table>
5.3 Results

The results confirm that a loss of mangroves occurred in all regions, primarily as a consequence of anthropogenic activities (Table 5.2, Table 5.3, Figure 5.3). As a proportion of the 1172 $1^\circ \times 1^\circ$ tiles examined, 12% were observed to have lost mangroves as a consequence of anthropogenic activity. Evidence of change that occurred prior to the acquisition of JERS-1 SAR data was observed in over 38% of tiles. The most common cause of mangrove loss (10% of all tiles) was conversion to aquaculture/agriculture, which was particularly prominent in Southeast Asia (8% of the total number of tiles). Mangrove loss as a consequence of natural processes (erosion) was evident in some regions (e.g. French Guiana) but colonisation/regrowth was more evident and widely distributed. Mangrove forest within the vast majority of tiles were observed to have remained intact over the time-series, even if previously disturbed. Approximately 10% of the tiles studied were highlighted as ‘hotspots’ of change, which should be prioritised for future monitoring. The distribution of these processes are shown in Figure 5.4.

The majority of the world’s mangroves were located in Southeast Asia (33.6%) which contained substantially more mangrove forest than the second largest region (Africa) with 20.8%. North America and South America had approximately equitable proportions of global mangrove forest extent, with 14.4% and 13.8%, respectively. Oceania contained 10.6% of the world’s mangroves with MEI containing just 6.8% of the global total.
### Table 5.2: Distribution and frequency (as a percentage) of mangrove forest change (gain and loss) 1996-2010. NA = North America (including Caribbean), SA = South America, MEI = Middle East and India, SE Asia = Southeast Asia.

<table>
<thead>
<tr>
<th>Change/Region</th>
<th>NA (%)</th>
<th>SA (%)</th>
<th>Africa (%)</th>
<th>MEI (%)</th>
<th>SE Asia (%)</th>
<th>Oceania (%)</th>
<th>Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agri/aquaculture</td>
<td>1.3</td>
<td>1.2</td>
<td>0.2</td>
<td>0.5</td>
<td>8.3</td>
<td>0.0</td>
<td>11.4</td>
</tr>
<tr>
<td>Erosion</td>
<td>1.8</td>
<td>4.9</td>
<td>3.7</td>
<td>1.6</td>
<td>5.0</td>
<td>3.4</td>
<td>20.4</td>
</tr>
<tr>
<td>Regrowth/Deposition</td>
<td>2.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>5.3</td>
<td>9.9</td>
<td>32.8</td>
</tr>
<tr>
<td>Logging</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>5.3</td>
<td>0.9</td>
</tr>
<tr>
<td>Dieback</td>
<td>0.1</td>
<td>0.1</td>
<td>0.3</td>
<td>0.0</td>
<td>29.1</td>
<td>11.4</td>
<td>34.4</td>
</tr>
<tr>
<td>Intact</td>
<td>13.7</td>
<td>4.9</td>
<td>9.1</td>
<td>3.9</td>
<td>2.5</td>
<td>1.6</td>
<td>25.8</td>
</tr>
<tr>
<td>Prior Disturbance</td>
<td>7.6</td>
<td>3.9</td>
<td>2.1</td>
<td>3.9</td>
<td>1.0</td>
<td>1.4</td>
<td>13.1</td>
</tr>
<tr>
<td>Hotspot</td>
<td>1.6</td>
<td>1.4</td>
<td>0.6</td>
<td>0.3</td>
<td>5.8</td>
<td>0.3</td>
<td>7.8</td>
</tr>
<tr>
<td>Table 5.3: Distribution and frequency (as a percentage) of mangrove forest change (gain and loss) 1996–2010 per proportion of mangrove in the region.</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>------------------</td>
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<td>------------------</td>
<td>------------------</td>
<td>------------------</td>
<td>------------------</td>
</tr>
<tr>
<td></td>
<td>Africa (%)</td>
<td>Global (%)</td>
<td>MEA (%)</td>
<td>Global (%)</td>
<td>Global (%)</td>
<td>North America (%)</td>
<td>Global (%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Mangrove Area (%)</td>
<td>56.8</td>
<td>56.8</td>
<td>56.8</td>
<td>56.8</td>
<td>56.8</td>
<td>56.8</td>
<td>56.8</td>
</tr>
<tr>
<td>Dieback (%)</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Prior (%)</td>
<td>4.6</td>
<td>4.6</td>
<td>4.6</td>
<td>4.6</td>
<td>4.6</td>
<td>4.6</td>
<td>4.6</td>
</tr>
<tr>
<td>Aquaculture/Agriculture (%)</td>
<td>3.8</td>
<td>3.8</td>
<td>3.8</td>
<td>3.8</td>
<td>3.8</td>
<td>3.8</td>
<td>3.8</td>
</tr>
<tr>
<td>Combined Anthropogenic</td>
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<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Combined Loss</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Erosion and Gain 1996–2010</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Pristine</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>No Change 1996–2010</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Erosion 1996–2010</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Anthropogenic 1996–2010</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Gain 1996–2010</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Loss 1996–2010</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
</tbody>
</table>
5.3. RESULTS

5.3.1 Combined loss and distribution of mangrove

Combined loss accounts for all causes of mangrove loss including those from 1996-2010 and losses inferred prior to 1996. Globally, the combined causes of mangrove loss occurred in $1^\circ \times 1^\circ$ tiles where 72.2% of the world’s mangroves were located. Regionally the largest proportion of mangrove area in a region with combined losses was the Middle East and India (MEI, 89.1%) and South America (88.9%) regions, accounting for 6.1% and 12.3% of the global proportion. The largest (24.8%) global proportion of mangrove area within $1^\circ \times 1^\circ$ tiles where combined causes of loss were identified was in Southeast Asia, whereby 73.8% of the mangrove area in the region was within an affected area. Africa, North America and Oceania contained global mangrove proportions coincident with combined losses of 14.1%, 9.1% and 5.8%, respectively. These contained regional proportions of 67.8%, 63.3% and 55.3%, respectively.

5.3.2 Combined anthropogenic impact

The combination of observed anthropogenic activity included loss of mangrove over and also prior to the observation period. The number of tiles (n) where human activities disrupted mangroves were greatest in Southeast Asia (52.6%, n = 235) followed by Oceania (16.6%, n = 29) and Africa (17.8%, n = 27) and was least in the MEI (1.3%, n = 15). Globally, 37.8% of tiles (n = 447) were affected by human activities. Globally, 40.9% of the world’s mangroves were located in a region where anthropogenic activity was identified. The largest area of mangrove as a proportion of the global total, within a region of anthropogenic disturbance, was located in Southeast Asia (18.3%), where over half (54.5%) of the mangrove area was within $1^\circ$ of an occurrence of anthropogenic loss. Lesser proportions of the global total mangrove area were affected in North America (8.3%), Africa, (4.6%), MEA (4.2%), South America (11.3%) and Oceania (1.7%). Although the global proportion of mangrove area within the MEI region within a region of anthropogenic disturbance was small (4.2%), of this 61.8% was within a region of anthropogenic loss at the regional level. Conversely, the global proportion of
Figure 5.3: Distribution of gain and loss in global mangrove forest extent occurring within a 1° tile.
5.3. RESULTS

Figure 5.4: Distribution of different drivers of change in mangrove forest extent across the tropics. A) Degradation from anthropogenic and natural drivers of change including evidence of prior disturbance B) Tiles that contained intact mangrove (1996–2010) C) Advance and regrowth of mangrove extent (1996–2010) D) Hotspots where substantial changes in mangrove forest extent were observed (1996–2010).
mangrove within Africa located within a region with anthropogenic change was marginally larger (4.6%) than MEI, although regionally this was a far smaller proportion (21.8%) in comparison.

5.3.3 Agriculture/Aquaculture

Mangrove loss through aquaculture and/or agriculture was identified in 134 (11.3%) tiles. The greatest proportion of these (72.4%, n = 97) occurred in Southeast Asia. These practices were also observed in Africa (1.5%, n = 2), MEI (4.5%, n = 6), North and Central America (11.2%, n = 15) and South America (10.4%, n = 14). No evidence of aquaculture/agriculture was observed in Oceania over the period of the time-series. Whilst this relays the geographical distribution of forest loss, it does not impart the scale on which the practice occurred. Some regions exhibited localised loss (i.e. Panama) whilst aquaculture on a far greater scale was observed in other regions (e.g. Mahakam delta, Kalimantan, Indonesia as illustrated in Figure 5.5). The largest area of mangrove as a proportion of the global total, within a region where aquaculture was observed, was located in Southeast Asia (11.9%), where 35.6% of the mangrove area in the region was within $1^\circ \times 1^\circ$ of an occurrence of aquaculture. Lesser proportions of the global total mangrove area were affected in Africa (10.8%), South America (1.6%) and North America (1.5%) with regional proportions of 51.7%, 11.57% and 10.7%, respectively. The global proportion observed was <1% in MEI and Oceania, with regional proportions of mangrove <6%.

5.3.4 Prior disturbance

Loss of mangrove prior to the 1990s were inferred and recorded in addition to change that occurred over the period of the time-series imagery. The largest prior losses were observed in Southeast Asia (n = 202) and accounted for 50.1% of the total number (n = 403) of tiles with observed losses globally. Similarly, prior loss as a consequence of anthropogenic impacts were observed in North and Central America (22.1%, n = 89), South America (11.4%, n = 46), Oceania (7.2%, n = 29), Africa (6.2%, n = 25) and MEI (3%, n = 12). As a proportion of the global
Figure 5.5: The conversion of mangroves to aquaculture at the Mahakam delta, Kalimantan, Indonesia. Mangrove degradation in the region was observed in the JERS-1/ALOS PALSAR colour composite imagery (Red = 1996 JERS-1, Green = 2007 PALSAR, Blue = 2010 PALSAR) and verified using Landsat imagery. a) Colour composite SAR image, b) 1996 Landsat 5 TM image, c) 2010 Landsat 5 TM image. The mangrove loss was identified using the distinct colour in the radar composite imagery and geometric shape of the change feature. The distinct red colour is a consequence of a decrease in radar backscatter in 2007 and 2010 from 1996 due to the replacement of a rough mangrove environment with the smooth surface of an aquaculture pond.

total that occurred within a $1^\circ \times 1^\circ$ tile with evidence of prior disturbance, 14% was located in Southeast Asia (regional: 41.5%). This was followed by North America (global: 8.1%, regional: 56.1%), MEI (global: 3.8%, regional:56.2%), Africa (global: 3.8%, regional: 18.2%), South America (global: 3.6%, regional: 26%) and Oceania (global: 1.7%, regional: 15.7%).

5.3.5 Erosion

Erosion was observed to have occurred globally (n = 239). The largest losses were in Southeast Asia (24.7%, n = 59) followed by South America (23.8%, n = 57), Africa (18%, n = 43), Oceania (16.7%, n = 40), North and Central America (8.8%, n = 21) and MEI (7.9%, n = 19). The majority of occurrences of erosion were observed in high-energy environments, such as along exposed coastlines and at the confluence of rivers and at river mouths. Erosion was widespread in the regions, with the largest global proportion of mangrove within a region where erosion was identified occurring within South America (global=11.3%, regional=81.7%) , Africa (global=10.8%, regional=51.7%) and Southeast Asia (global=10.3%, regional=30.8%). Globally, lesser proportions of mangrove area
were located within Oceania (global=4.6%, regional=43.9%), MEI (global=3.8%, regional=55.3%) and North America (global=3.4%, regional=28.3%).

5.3.6 Colonisation/Regrowth

The loss through erosion was offset by colonisation of coastal regions and the regrowth of previously disturbed forests. A total of 384 tiles exhibited colonisation/regrowth of which the majority (39.3%, n = 151) occurred in Southeast Asia. Lesser occurrences of colonisation/regrowth were observed in Oceania (16.1%, n = 62), South America (15.6%, n = 60), Africa (15.6%, n = 60), MEI (7%, n = 27) and North America (6.7%, n = 24). As with erosion, the majority of advance was observed in high-energy environments as eroded sediment was deposited in sheltered regions along coastlines and within river reaches. An example of this process occurring in French Guiana is shown in Figure 5.6. The largest proportion of the global mangrove forest extent (19.9%) within a $1^\circ \times 1^\circ$ that contained evidence of mangrove gain was within Southeast Asia (regional: 59.2%). A large global proportion also occurred in Africa (global: 15.6%, regional: 74.9%) with lesser quantities in South America (global: 11.7%, regional: 84.6%), Oceania (global: 5.7%, regional: 53.9%), MEI (global: 3.8%, regional: 55.7%) and North America (global: 3.8%, regional: 55.7%).

5.3.7 Dieback

Dieback was not observed to any great extent but occurred most frequently in Southeast Asia (61.1%, n = 11), followed by Africa (22.2%, n = 4) with each of the remaining regions containing a single occurrence, with the exception of MEI (n = 0). Dieback contributes to a small portion of mangrove degradation (1.5%) globally. As a proportion of the global mangrove area, dieback did not occur within a $1^\circ$ tile of a large mangrove area, with the largest area in Africa (4.9%), followed by Southeast Asia (3.7%). The occurrence of dieback in MEI, North America, Oceania and South America was coincident with <1% of the global forest area.
Figure 5.6: Mangrove advance along the French Guiana coastline. Mangrove advance in the region was observed in the JERS-1/ALOS PALSAR colour composite imagery (R = 1996 JERS-1, G = 2007 PALSAR, B = 2010 PALSAR) and verified using Landsat imagery. A) JERS-1/PALSAR colour composite image, B) 1997 Landsat 5 TM image, C) 2010 Landsat 5 TM image. The advance was identified due to the colouration of the feature in the radar composite image and its context along the coastline. The distinct blue colour is a consequence of enhanced radar backscatter in 2010 due to the rough texture of a mangrove environment over that of the smoother surface of the ocean in 1996 and 2007.

5.3.8 Intact

From the total number (1172) of tiles, intact mangrove extent that had not been disturbed over the period 1996-2010 was observed in the majority (71.6%, n = 840). The largest number of tiles categorised as unchanged were present in Southeast Asia (40.6%, n = 341). This was followed by North America (19%, n = 160), Oceania (16%, n = 134), Africa (12.7%, n = 107), South America (6.9%, n = 58) and MEI (5.5%, n = 46). Total intact mangrove area within the extent of a 1° × 1° tile was 30.4% and exhibited no evidence of negative changes over the period 1996–2010 or of negative changes prior to 1996. The largest global proportion of intact mangrove area was located in Southeast Asia (11.4%) with a regional proportion of 33.9%. The largest regional proportion of mangrove area within an intact region was located within Oceania (44.7%), although this accounted for just 4.7% of the global proportion. The regional proportions of area within 1° × 1° of intact mangrove in Africa, MEI, North America and South America were 32.3%, 10.9%, 36.7% and 11.1% respectively. These occupied a small proportion of the global areas of mangrove of 6.7%, 0.7%, 5.3% and 1.5%, respectively.
5.3.9 Accuracy assessment

Using the 1172 tiles, changes in mangrove forest extent were successfully documented across the world with an overall accuracy of 89% (Table 5.4, kappa coefficient 0.85). The class accuracies for both erosion and deposition/regrowth were high with little class confusion reflecting the ease and reliability at which these causes of change were observed, providing a tractable way through which other similar global assessments of land cover change can be conducted.

Table 5.4: Accuracy of identifying a change process within mangrove forest extent 1996–2010.

<table>
<thead>
<tr>
<th></th>
<th>Intact</th>
<th>Disturbed</th>
<th>Aqua/Agriculture</th>
<th>Erosion</th>
<th>Deposition/Regrowth</th>
<th>Logging</th>
<th>Total</th>
<th>User’s Accuracy</th>
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</thead>
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<td>3</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>38</td>
<td>74</td>
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<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>100</td>
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<td>0</td>
<td>1</td>
<td>26</td>
<td>0</td>
<td>0</td>
<td>29</td>
<td>87</td>
</tr>
<tr>
<td>Deposition/Regrowth</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>27</td>
<td>0</td>
<td>28</td>
<td>86</td>
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<tr>
<td>Logging</td>
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<td>0</td>
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<td>10</td>
<td>10</td>
<td>160</td>
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<tr>
<td>Producer’s Accuracy</td>
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<td>83</td>
<td>87</td>
<td>90</td>
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</tr>
</tbody>
</table>

5.4 Discussion

Changes in mangrove forest extent were observed across their range as a consequence of both natural and anthropogenic drivers. The natural processes of erosion and deposition caused mangrove retreat and colonisation/regrowth, respectively. Although erosion was observed in a large proportion (20.2%) of tiles, this was counteracted by the colonisation of mangroves in 32.4% of tiles. In some areas, erosion and colonisation were extensive. For example, along the French
Guiana coastline, Fromard et al. 2004 measured a change in mangrove extent of 125.4 km$^2$ over the period 1951–1999 with this attributed to both erosion and accretion of sediment. A portion of this change was observed in the colour composite imagery as illustrated in Figure 5.6.

The influence of anthropogenic activities upon mangrove forest extent over the period of observation was substantial, with greater than 10% of tiles affected. This reinforced the observations that conversion of mangroves to commercial forms of food and resource production has been widespread. Dewalt et al. 1996, PÁez-Osuna 2001, Tong et al. 2004. The majority of loss and degradation occurred in Southeast Asia where aquaculture practices are extensive. This is due to the enormous global demand on marine products and the ability for aquaculture to provide a means of attaining food security, both in terms of national consumption and income generation through exports in developing nations. Ahmed and Lorica 2002. Aquaculture/agriculture was readily observed in the JERS-1 and ALOS PALSAR composites due to the geometric shape (straight edges, square and rectangular shaped patterns) associated with aquaculture ponds and plantation boundaries and the contrast in radar backscatter between a rough mangrove forest environment and a smooth pond surface. The colour of the imagery was less distinct for agriculture than aquaculture due to the similar backscatter properties between mangrove and terrestrial vegetation canopies. The detection of agriculture was, therefore, dependent upon the period between the removal of the mangrove and growth of the crop/plantation and when the radar data were acquired.

Although loss and degradation of mangroves between 1996 and 2010 was substantial, this only partially revealed the extent of historic anthropogenic impact upon mangroves. The colour composite imagery enabled disturbance that occurred prior to 1996 to be inferred. This was evident in the imagery by non-natural mangrove boundaries that had no distinct colouring. An example of this is aquaculture that formed geometric shapes within the mangrove but had no distinct colour from the composite imagery as they occurred prior to the earli-
est image (Figure 4B). Often, such activities were verified using earlier Landsat sensor data (Figure 5.1). Disturbance in excess of 35% of all tiles, reaching a regional maximum of 50%, is in keeping with the observed trend of substantial mangrove degradation and loss across their range (Duke et al., 2007; Polidoro et al., 2010).

The majority of change in mangrove extent occurred in Southeast Asia. Within this area, industrial shrimp farming has been advocated as a method of obtaining foreign exchange earnings, funding external debt, promoting development, reducing poverty and increasing food security through economic growth in coastal indebted poor countries (Rivera-Ferre, 2009). This has led to developing nations supporting almost 90% of global production of farmed seafood consumed worldwide (UNFAO, 2014). However, whilst total anthropogenic disturbance occurred in 49.6% of tiles in Southeast Asia, this was marginally larger than 46.9% of tiles in North America. Despite fewer occurrences (n = 145) in North America, the impact of anthropogenic activity at the regional level was just as substantial, with developed nations responsible for the historic clearing of mangroves for large urban developments (i.e. Florida) (Teas, 1977). This highlights that mangrove loss and degradation is widespread and not geographically constrained and therefore, the results of the global assessment must be evaluated at the regional scale. The frequency of loss and degradation, however, does not impart the areal extent of the degradation as the motive for the removal of mangrove forest can vary from small-scale clearing for localised use to industrial-scale clearing.

The assessment of $1^\circ \times 1^\circ$ tiles revealed the distribution of drivers of change in mangrove forest extent but did not provide an indication of the distribution of mangrove forest extent that may be affected. The calculation of the proportion of mangrove forest within each $1^\circ \times 1^\circ$ tile, derived from the mangrove map of Giri et al. (2011), provided the quantity of mangrove that was located within a region that is undergoing a change. Whilst this did not provide any information on the area of the change that occurred, it did indicate the quantity of mangrove that was located within a $1^\circ \times 1^\circ$ tile where a driver of change was present. This
indicated the proportion of global mangrove extent that may be at risk.

The low percentage of mangrove forest proportion within $1^\circ \times 1^\circ$ tiles that was completely intact indicates that the vast majority of mangrove extent was within a region that was undergoing at least one driver of mangrove loss. This places a large proportion of the world’s mangrove forest extent within a potentially ‘at risk’ region. The anthropogenic causes of loss were identified within $1^\circ \times 1^\circ$ tiles where 40.9% of the world’s mangroves were located. Although anthropogenic activity was identified in 12% of the tiles, these drivers were present in $1^\circ \times 1^\circ$ tiles that contained 40.4% of the world’s global mangrove extent. The majority of this (18.3%) was located in Southeast Asia which contained the largest proportion of global mangrove forest. Other regions contained a human driver of loss within a $1^\circ \times 1^\circ$ tile that had a large proportion of mangrove at the regional level, such as MEI (61.8%), although the proportion of mangrove at the global level was small (4.2%).

Additional losses identified as having occurred before the time-series colour composites, prior to 1996, did not increase the proportions of mangrove that were coincident with the driver of change. This indicated that anthropogenic causes of mangrove loss were located in regions where historic mangrove clearing had occurred. This is plausible as in many instances, aquaculture practices are built where previous infrastructure is located. This also suggested that pristine mangrove outside of these areas were not immediately at risk, as anthropogenic practices had not ventured into new pristine regions since at least 1996. It is likely that mangrove conservation strategies and forest reserves have been responsible for this. This data could be used to implement additional legislation to preserve a guaranteed minimum mangrove forest extent.

The results of the distribution of mangrove forests reveal that 59.7% of mangrove forest extent were located in $1^\circ \times 1^\circ$ tiles that exhibited evidence of colonisation or regrowth, although it does not provide the area of regrowth/colonisation that occurred. As the area of change is unknown, if the colonisation/regrowth occurred in the same tile as large anthropogenic clearing, as in Kalimantan, then the
colonisation was dwarfed by that of the occurrence of anthropogenic degradation. Conversely, erosion occurred in $1^\circ \times 1^\circ$ tiles where 44.2% of global mangrove forest extent was located. Erosion and regrowth occurred simultaneously in regions that represented 64.2% of the world’s mangrove forests.

The statistics generated have both regional and global importance. At the regional level, the proportion of mangrove that was within a $1^\circ \times 1^\circ$ tile where a driver of change was identified was disproportionately greater where the global proportion of mangrove forest was smaller. Although, the driver of change may coincide with a greater proportion of mangrove at the regional level, its importance as a proportion of the global total was diminished. This was evident in the proportion of mangrove that occurred within a $1^\circ \times 1^\circ$ tile with evidence of anthropogenic loss. Within the MEI region, the regional proportion of mangrove with an occurrence of anthropogenic loss was 61.8% whilst within Southeast Asia it was 54.5%. However, at the global level the proportion of mangrove in MEI accounted for 4.2% of the global proportion and 18.3% of the global proportion within Southeast Asia. This does not diminish the elevated proportion at the regional level within MEI, as although the mangrove proportion was less significant at the global level, the increased proportion at the regional level could serve as an indicator of the critical condition of mangrove forest extent within this region. It is, therefore, important that both proportions of mangrove forest at the regional and global level are considered.

The methodology used implemented a simple framework for assessing land cover changes and observed threats to mangroves over large areas. This method enabled the drivers and distribution of mangrove forest degradation to be inferred globally over a 14-year time period, revealing regions with the greatest occurrence of loss and degradation of mangroves. Whilst mangrove extent was not explicitly mapped, this is the first study to provide information on the causes and distribution of the threats and degradation upon global mangrove forests. Whilst this approach implemented a method subject to interpreting error, it has the potential to be repeated annually with the continued acquisition of JAXA’s
ALOS-2 PALSAR-2 and ESA’s Sentinel-1 SAR imagery. An interpreter is also able to exploit contextual information, including the straight-edge geometry of aquaculture practices, which are difficult to implement using computer-vision algorithms.

Gradual changes at the landward margin or within the mangrove forest were the most difficult to observe due to the low contrast in backscatter between images, especially where the change occurred at a sub-pixel level (< 25 m). Conversely, changes at the seaward margin or the conversion of mangrove to aquaculture were the most readily observed due to the contrast in backscatter between the land and water in radar imagery.

The accuracy assessment revealed encouraging results (overall accuracy of 89%, kappa coefficient 0.85), indicating a high degree of correspondence between the L-band radar and Landsat-based assessments of change. This method, therefore, provides a tractable tool for monitoring broad scale land cover changes over the range of mangroves. However, the accuracy of mangrove dieback could not be determined because this process was not readily identifiable in the time-series of optical satellite imagery and was omitted from the accuracy assessment. In addition, the spatial resolution of the imagery (25 m) limited the detection of all areas of mangroves occupying small localised areas.

A potential source of confusion occurred where rough water surfaces, due to wind and storms, increases backscatter over water bodies resulting in similar backscatter properties to land surfaces such as forest. Changes in water surface roughness through time can, therefore, be misinterpreted as a change in mangrove forest, due to the variations in backscatter. This was of little consequence over the ocean and within rivers as such large bodies of water were readily identified, but was more difficult to decipher when occurring over inland water bodies (aquaculture ponds/small lakes). These occurrences were rare but in such instances the geometric shape of the area of loss/gain was used to aid the interpretation.
5.5 Conclusions

The assessment of the drivers of change upon global mangrove extent across the globe revealed the distribution of these drivers and indicated where drivers of concern were concentrated. Further to this, the assessment of the distribution of mangrove forest extent from Giri et al. (2011) with the drivers of change revealed the proportion of global mangrove extent that was within a $1^\circ \times 1^\circ$ tile of a driver of change. As the drivers of change were not evenly distributed, these statistics unveil the global proportion of mangrove forest that the distribution of drivers of change may affect. Despite this, the areas of mangrove loss and gain as a consequence of the drivers of change, could not be accurately mapped. This method could not provide information on the area of mangrove change and was, therefore, limited in its ability to describe the changes that have occurred in mangrove extent over the period 1996–2010. This work highlighted the need for a global monitoring system that is able to map both the areal extent of the existing mangrove forest and the regions of change. Without this data, the gain and loss of mangrove extent cannot be compared and accurate information as to whether mangrove forests are in net growth or decline cannot be retrieved.
Chapter 6

Mapping Mangrove Extent

This chapter provides a description of the method to update the mangrove map of the world at the selected study locations. The chapter describes the collection of training data and its use within a machine learning algorithm. The results are presented and discussed and the main conclusions are stated at the closing of the chapter. The structure of the chapter is presented in Figure 6.1.

Figure 6.1: High level workflow outlining the steps towards achieving a classification with respective sections in the chapter.
6.1 Method

The method follows a typical approach to a supervised classification, namely the subsetting of data, the collection of training data and the application of a classification algorithm. These steps are outlined in the following sections and follow the overview workflow provided in Figure 6.2.

Figure 6.2: Workflow of pre-processing, collection of training data and classification steps and their respective sections within the chapter.

6.1.1 Defining a mangrove habitat

The segmentation of satellite images over large areas can create a large number of objects (>10,000,000). In order to target only those objects that are potentially mangrove, a mangrove habitat area was derived for each scene. This was done by analysing the physical characteristics of a mangrove forest within its environment, using a combination of datasets. Mangrove forests, like many other terrestrial vegetation, exist within an ecological niche under preferred environmental conditions that are often defined by the physical characteristics of their surroundings. Specifically, mangrove forests inhabit the low lying coastal areas within close proximity to water. Mangroves are not found at high elevations and at great distances from water, due to the sensitivity of mangroves to temperature and their intolerance to arid environments. A mangrove habitat region was, therefore, defined by evaluating the relationship between the known mangrove extent and the characteristics of the environment in which they are situated. This was achieved through a combination of the existing map of mangrove forests and datasets that describe the physical characteristics of the environment (Figure 6.3). These datasets were elevation, slope and distance to water.
6.1. METHOD

Figure 6.3: A mangrove habitat can be described by the physical characteristics of existing mangrove forests. These characteristics are elevation, slope and distance to water and are combined to define an area by which to subset the radar imagery for each study site.

6.1.1.1 Elevation

Mangroves require saline water and so are unable to grow in regions of high elevation that are above floodplains and not accessible by saline/brackish water. To represent this, the Shuttle Radar Topography Mission (SRTM) digital surface model (DSM) elevation dataset was used. The SRTM records the height of the mangrove canopy inclusive of the ground elevation. This is intended to represent the maximum height at which mangroves would occur, whether it be the elevation of the ground or mangrove height alone, or a combination of both the ground elevation and mangrove height. Regardless, no mangrove would be sought above this maximum threshold.

6.1.1.2 Slope

It is assumed that mangroves are unable to grow in areas with steep slopes but on flat lowland wetlands with greater access to saline/brackish water. In order
to test this, statistics that describe the slope of existing mangrove forests were extracted. The slope dataset was generated using the SRTM DSM using GDAL. As the elevation dataset was a DSM, the elevation values within it are those of the vegetation canopy and not Earth’s ground surface. It became apparent that this prevented slope from being a useful descriptor of the mangrove environment as the transition from water to tall vegetation caused a false increase in slope (Figure 6.4). Slope was, therefore, discounted as a descriptor of the mangrove environment.

![Figure 6.4: The difference in elevation between the water surface and vegetation canopy causes a false slope that makes this unusable as a descriptor of the mangrove environment.](image)

6.1.1.3 Distance to water

Mangrove forests are a salt tolerant species and are able to thrive in saline environments where other terrestrial species cannot. As a consequence mangroves are often characterised by their close proximity to saline water, commonly growing along the tidally inundated shorelines of tropical countries. To retrieve the relationship between mangrove forests and their proximity to saline water, a sea mask had to be generated from the ALOS scenes. The sea mask was generated using GDAL and RSGISLib and was implemented in python. A threshold was set on the backscatter of the HH images (<-15) and on a corresponding SRTM DSM (≤5) through manual optimisation. A HH backscatter value above -15 was too
6.1. METHOD

high as it began to encroach the sea margin inland whilst a value lower than this was below the backscatter caused by ocean waves. An elevation above 5 m introduced error into the sea mask from excessive inland water bodies whilst a value below this limited the reach of the rivers inland. This resulted in a binary image of sea extent that also included some low lying inland water bodies (i.e. aquaculture) and flat bare regions inland, that had a low backscatter. Inland water bodies and bare ground were separated from the ocean by combining homogeneous regions of adjacent pixels into individual objects (clumps) and intersecting these with a crude manually drawn sea extent. The intersection of these two datasets yielded only the ocean extent, absent of inland water bodies and bare ground. GDAL was used to calculate the distance of the land pixels in the binary image from the ocean pixels, calculating the distance of each pixel in the scene to the nearest target pixel (ocean).

6.1.1.4 Mangrove habitat statistics

In order to generate statistics that describe the distribution of the known mangrove extent in its environment with respect to its physical properties, information on the height and distance to water of the mangrove forest had to be extracted. This was done using RSGISLib by extracting the image pixel values from a dataset using a target zone in the form of a raster. The target zone was defined by the existing mangrove map by Giri et al. [2011] and the data extracted was from the distance to water images and the SRTM elevation data. The distributions of the data are shown in Figure 6.5 and Figure 6.6.

The investigation into the distribution of mangrove with elevation and distance from water indicate that mangrove forests are located with preference for certain environmental characteristics. The extraction of the distance from water values indicated that the majority (99%) of mangroves studied occur within 30 km of the coast. This was expected given the known attributes of mangroves as riparian vegetation that are adept to thriving in saline regularly inundated environments. The distribution exhibits a clear relationship between mangrove distribution and distance to water with the largest frequency occurring nearest to the coast and
CHAPTER 6. MAPPING MANGROVE EXTENT

Figure 6.5: Distribution of distance of mangroves from water, derived from zonal statistics.

Figure 6.6: Distribution of elevation of mangroves, derived from zonal statistics.
decreasing with increasing distance away from the nearest water source. The distribution of mangroves with height reveals a similar trend in that the majority of mangroves are of a low height and decrease in frequency with increasing height. The 99th percentile for mangrove height was 33 m. Unlike the distribution of mangrove forests with distance from water, the distribution with height increases to a maximum value before decreasing. This is an artefact of the SRTM which is a digital surface model and records elevation values inclusive of that of the ground and vegetation height. This does not provide specific information on mangrove tree height, but provides a maximum threshold value, composed of a combination of ground elevation and mangrove height, beyond which no mangrove is sought. Deriving a realistic relationship between mangrove distribution and elevation is therefore challenging.

Prior to the classification, the input images were masked to within 30 km of water and to an elevation of 33 m to reduce data redundancy by not including regions where mangroves could not plausibly occur. This would reduce error by removing inland areas where misclassification of the imagery could occur.

6.1.2 Generation of training data

The currently available global mangrove maps (outlined in Section 4.5) can be used to extract training data from the input ALOS PALSAR and Landsat mosaic imagery, enabling a large quantity of training data to be collected, representing a range of mangrove species and growth stages. Despite this, the maps were defined from data collected over the last half-century, over which period mangrove extents would have changed. This would introduce erroneous training data into places where mangroves had retreated or been removed and would fail to represent new advances of mangrove. Any error as a consequence of class confusion within the map would also introduce error into the training dataset. In order to refine this dataset, a Bayesian maximum–likelihood classification approach was used to reclassify within the combined existing mangrove extent, using the combined dataset to weight the classification. This a priori dataset was generated through a combination of multiple existing maps into a single map, whereby the
extent of mangrove common to more than one map was given a higher weighting and the occurrence of mangrove in one map was given a lower weighting. The generation of this dataset is outlined in Section 4.5. The use of this dataset within a Bayesian maximum–likelihood approach would update the existing map to 2010 and make it suitable for the collection of training data for the reclassification of the mangrove extent. The refinement of the existing map for a training mask could not be used as a final product as this would not take into account the mangrove extent outside of the existing maps.

6.1.2.1 Bayesian maximum–likelihood classifier

The Bayesian maximum–likelihood classifier is derived from Bayesian statistics, which unlike traditional tests of probability, whereby all input variables are treated equally, allows for the input of variables that provide the classifier with evidence that is capable of influencing the result.

In terms of image classification, traditional probabilistic methods calculate the class probability based upon the input image values and assume that class probability is equally spatially distributed. However, mangrove forests are a land cover for which its distribution is defined by the physical characteristics of its environment. In this case, the likelihood of class occurrence is not equally distributed across a scene. A Bayesian maximum–likelihood approach is able to accommodate the requirements of the desired classifier in that it is applicable to a series of independent study sites and is flexible enough to be influenced by inputs that are under the user’s control. This enables the use of the contextual characteristics of the mangrove class to be maximised whilst ensuring the method does not rely upon user defined thresholds which may vary spatially.

A maximum–likelihood classification algorithm calculates the probability of each image pixel/image object occurring as a member of a given class where \( n \) number of classes are provided. The algorithm requires training data which provides the classifier with the distribution of spectral values for each class and then deduces the probability of each value occurring within the training data, assuming the distribution of the training data is normal. Once the probability for each class
Figure 6.7: An example of how probability is derived for values in the range 3.5-4 and 5-7. The larger range between values and thus larger area under the PDF yields a greater probability.

has been evaluated, the image/object value is assigned to the class with the highest probability. The probability of the occurrence of an event is equitable to the area it occupies under a probability distribution function (PDF). A pdf is a function that describes the likelihood that any given random variable will occur, within the limits of the given function. This is deduced by the integral of the range over which the value occurs, whereby the integral of the entire range of the function is equal to one and is non-negative everywhere. This integral of the pdf is known as the cumulative density function (CDF) and occurs over the range negative infinity to the value at which it is calculated. The likelihood of a given pixel value occurring is given by the area it occupies under the CDF, a function of the integral over its range and not its location under the pdf. The probability of a single value occurring is small as the area it occupies is small. A value within a range occupying the full range of the function would be a certainty. This is exemplified in Figure 6.7.

An object composed of mangrove forest pixels is assumed to have a range of values similar to that of the training data, therefore occupying a large area under the CDF and having a high probability of belonging to the mangrove forest class.
Conversely, a water object will have a different range of values to that of the range of the mangrove training data and will occupy little if any of the area under the CDF and will have a low probability of belonging to the mangrove class.

A Bayesian maximum-likelihood classifier allows an *a priori* dataset to influence the classification. The prior can be utilised in a number of potential ways, which vary in how the prior is calculated. Furthermore, the maximum-likelihood algorithm can be applied to varying proportions of the image, dependent on whether the whole scene, mangrove extent of [Giri et al. (2011)](#), or both is classified. The advantages and limitations of the use of the prior and extent of the classification in a variety of combinations are outlined below.

### 6.1.2.2 Option 1

One option was to segment the entire scene and apply the classification to all of the image segments, using the characteristics that describe the context of mangrove forests in their environment as prior knowledge. Data layers such as the proximity of mangrove to water and the proximity of unclassified segments to the existing mangrove extent could be generated. However, this approach would have a number of limitations. Although the priors could be generated scene by scene, representing the context of an environment in such a way does not necessarily represent the distribution of the mangrove in reality. The method also suffers from the dilemma of how the distance from water and distance from mangrove priors should be characterised and weighted. Assigning probability values to such priors is arbitrary, as each object must be positively or negatively influenced based upon its location in the context defined by the priors. This approach would also apply the priors and algorithm to the whole scene, although the probability of mangroves occurring at high elevations and at large distances from water would be low.

### 6.1.2.3 Option 2

The limitations encountered in Option 1 can be alleviated by limiting the segmentation to that of small area and using a prior derived from the existing mangrove
6.1. METHOD

extent. These can be combined in such a way that the application of the algorithm and the prior is to only the extent of the combined existing maps. This reduces the area to be classified and would reduce the occurrence of misclassified mangrove objects. As the prior is composed of a combination of the existing baselines, the requirement for probabilistic priors that try and describe the characteristics of the mangrove environment are no longer required. This prior assumes that the objects already belong to the mangrove class and that a high probability from the prior will support this, whilst if the object has a low probability of being mangrove based upon its spectral properties, then this allows for its reclassification. Although the prior is more representative of mangrove distribution in reality and will work with the probability derived from the classification algorithm, it is limited in that mangrove forest missing from the original classifications, or that which has grown since, will remain unclassified.

6.1.2.4 Option 3

The third option utilises the strengths of option 1 and option 2 to classify mangrove extent using a suitable prior whilst enabling additional mangrove to be included. The whole mangrove habitat area is segmented and the prior used is that derived from the combined maps (Section 4.5). The prior and classification algorithm is applied only to the maximum extent of the existing baselines within the wider segmented mangrove habitat. Region growing could be used to classify objects between the existing extent and water as mangrove, on the assumption that these objects are new growth. Unclassified objects that are not between the mangrove and water, are not classified. Mangrove that is located inland and outside of the existing extent is assumed to be represented by the training data collected using the existing extent. This mangrove, whether mature or new growth, would be represented by the grown existing extent.

6.1.2.5 Segmentation

The segmentation algorithm implemented was that of Shepherd et al. (2013). The segmentation uses k-means clustering to generate cluster seeds. Pixels are then assigned to their respective clusters and are eliminated if they are below a user
specified minimum mapping unit (mmu). The eliminated clusters are assigned to the nearest neighbour cluster that is most spectrally similar. When all clusters below a defined mmu are assigned to a neighbour, the objects are given an ID and are labelled consecutively. The segmentation is implemented within RSGISLib using a python module and is dependent upon 2 key parameters. These are 1) the number $k$ of seed clusters and 2) the minimum number of pixels (minimum mmu) that each cluster should contain $n$. The smaller the value of $k$, the larger the objects that are produced. A smaller value of $n$ would allow smaller objects to be generated than a larger value of $n$. The segmentation was implemented on the Lee filtered dB radar imagery, using a combination of the HH and HV to maximise the homogeneity and heterogeneity to form meaningful image objects. The $k$ parameter was set as 4 and the $n$ parameter was set at 80 for all segmentations. This produced segmentations with a large number of objects, but was necessary to ensure that small enough objects were created to capture the detail of the mangrove extent.

6.1.2.6 Populate segments

The KEA file format supports a raster attribute table (RAT). This is a table whereby each row of the table is a unique object within a segmented image. Each row has a unique ID so that each image segment can be referenced. The columns of the RAT contain any user defined variable that can be represented as a raster. Examples of such data could be spectral reflectance values, elevation and even thematic information such as an existing land cover classification. Each image object can then be characterized, described and queried on the values in the columns in the RAT. The image objects are populated using bespoke commands within RSGISLib where the user can specify how the object is populated from a range of basic mathematical descriptors. These include the mean, maximum and minimum, amongst others, deriving the values from the pixels covered by each image object.

The information populated into the RAT included maximum and minimum radar backscatter, NDWI and NDVI values for each object, in addition to the mean a
priori dataset value and the mode value of a sea mask that was merged into the segmentation as a single object. The sea mask was merged in as an object as water was removed from the Landsat composite mosaic and so no training data could be generated for it. Subsequently, the use of probability to separate water and mudflats using radar data alone proved difficult due to the variation in ocean surface roughness, commonly causing a confusion between the classes. As the separation of these classes was not of interest to the project it was more efficient to treat them as a single class, from which mangrove change could be detected at a later stage. The sea mask generated from the ALOS PALSAR scenes for the mangrove habitat statistics did not differentiate water from mudflat and was reused for this step.

6.1.2.7 Collection of training data for maximum-likelihood classifier

For each location a number of land cover classes were identified using a combination of Google Earth imagery and the optical and radar datasets. The optical and radar datasets were used to ensure that the training regions represented the appropriate classes in the imagery that would be used in the classification whilst the Google Earth high resolution imagery aided the identification of classes. As a consequence of the coarse resolution of the data, land cover types that occur over large areas forming homogeneous areas and unfamiliarity with the majority of the sites, broad land cover classes were identified. Common land cover types included mangrove, rainforest, plantation, urban, bare soil and water. Often, more than one mangrove class was required, to account for the variety of mangrove growth stage. These include new colonising mangroves that have much smaller structure and subsequent backscatter than mature mangrove forest. Similarly juvenile mangroves and those of a lower biomass species that form on the landward margins of mangroves, particularly on fringes that form on large open mudflats, were represented separately. These were spectrally distinct in NDVI, NDWI and backscatter to form two additional mangrove classes.

To create the training polygons, Google Earth imagery was streamed into QGIS, an open source GIS software. Each radar image in the dataset for the year
2010 was overlayed on the optical background, along with the NDVI and NDWI images. Once the training polygons for each land cover class were created they were converted into rasters using GDAL. The training data were then extracted from an image stack composed of the HH and HV backscatter, NDVI and NDWI using the rasterised training areas. These were extracted using RSGISLib which records every pixel value that falls within the extent of the training area. This is advantageous over zonal statistics offered by proprietary software which creates an average value for each polygon extent. This enables a large training dataset to be collected.

A Bayesian maximum-likelihood approach assumes that the training data is normally distributed. To ensure this was implemented as accurately as possible, the distribution of the training data compared against a normal function plotted using the statistics from the distribution. In cases where the training data were found to be insufficiently normally distributed, anomalous polygons were removed and additional data representing that class were acquired. This provided a method of ensuring that the training data was normally distributed, offering an advantage over the implementation of the maximum-likelihood algorithm in proprietary software which relies on an assumption of the normality of the distribution of the training data.

6.1.2.8 Application of the Bayesian maximum-likelihood classifier

To attain the probability of the object occurring to each class the SciPy normal statistics module was used. This requires parameters that describe the distribution of the training data (mean and standard deviation) and the values to integrate (upper and lower image object values). The training data was read in from the file created during the collection of the training data. A normal distribution was then fitted to the data using the mean and standard deviation for the distribution.

This was then used to retrieve the integral of the lower value in the range of the object and subtract it from the integral of the upper range value. This produced a single value of probability that was equitable to the area under the
CDF defined by the integration of the PDF. This process was repeated using the training data for each class, with each probability value derived written into the RAT. The reading of the training datasets, fitting of the training distribution and calculation of the probability of each object for each class was all automated using Python.

Following the calculation of the probability of each image object occurring in each class, the probabilities were normalized before the \emph{a priori} data were applied. The prior calculated from the combination of the existing maps was applied by multiplying the probability of the mangrove class with that of the mean prior value for each object. The probabilities for each class were normalised once the prior had been applied.

To calculate the maximum-likelihood of each object belonging to a given class the probability for each object in each class was gathered and the maximum value was derived. Dependant upon the class within which the highest probability occurred, the name of the given class was attributed to the object. This was then written into the RAT forming a ‘classification’ column. The classes were then given colours to represent the land cover types.

All stages of the classification, from populating the empty RAT to colouring the classes was carried out in python, relying only upon open source software accessed through python modules. This ensured that the classification was scalable and was not restricted by input image sizes and that as many of the steps were as automated as possible. These advantages enable the classification to be run on high performance computers, offering the potential to apply the classification to large areas providing that the input data is available.

\subsection{Region growing}

A limitation of classifying within the extent of the combined \emph{a priori} dataset was that the mangrove extent may have changed since the dates of the imagery used in the creation of the baseline. Mangrove loss would have been detected by the maximum-likelihood classifier but there would be no method of classifying
mangrove extent that advanced and grew from the existing baseline. These new regions provide important training data because as they are younger mangrove, their spectral properties and backscatter may differ from that of mature mangrove. In order to adequately classify the entirety of the mangrove extent, it is important that mangroves of all ages are represented. The classified mangrove extent was extracted from the RAT using RSGISLib into a binary image and was populated into a chessboard segmented image of the study site, composed of 1 ha squares. This was done to eliminate an artefact of the segmentation whereby the position of objects within their environment is confused where the objects wrap around one another (Figure 6.8). The classification was populated into the gridded segments using the mode, so that only grid squares that contained a mangrove majority were assigned as mangrove objects. The region growing was implemented within RSGISLib and used thresholds on HH backscatter and distance to the water class to grow the classified mangrove extent towards the ocean. Prior to this, inland water bodies were removed from the classification so that mangrove extent would not grow towards inland water bodies, such as lakes. In a limited number of places, urban areas were grown into if they were situated along the coastline. A threshold on NDVI was therefore used to remove such regions using an implementation of the change detection outlined in Chapter 7. It was assumed that all vegetation with a sufficient backscatter that lay between a classified mangrove object and the ocean would also be mangrove, with the likelihood of it being another vegetation class being low.

An overview of the steps taken thus far is presented in Figure 6.9.

6.1.3 Reclassification of mangroves

The maximum-likelihood classification algorithm was able to refine the existing mangrove baseline for the collection of training data, but was inappropriate to use for classifying additional mangrove outside of what exists and the non-mangrove classes in the scene. The mangrove extent derived from the maximum-likelihood stage could, therefore, be used to extract a large training dataset although. A large number of other land cover types in the scene would also need to be classified
Figure 6.8: The irregular shape of the yellow object which wrap around others prevent the grow region from working. The yellow object could be grown into if it is between mangrove and water but the objects enveloped by it would not be between the leading mangrove edge and water and would not be classified as mangrove.

despite not being of interest. These are grouped together as an ‘other’ class which is composed of many different land cover classes which will have a non-normal distribution in the feature space, making the use of a maximum-likelihood classifier inappropriate.

To use the training data appropriately, a classification algorithm is required that is insensitive to the class distribution and the density of the class clusters within the feature space. A classification algorithm without these constraints has a number of additional advantages. Firstly, the non-mangrove classes do not need to be separated as their class distributions will no longer affect the classification. This is particularly useful when generating a method that is globally applicable as gathering training data for individual classes that are inferred and not known is time-consuming and challenging. Secondly, ensuring that training data gathered from composite imagery is normally distributed is a difficult and time consuming task that is no longer required.

6.1.4 Machine learning classification

6.1.4.1 $k$-NN vs Random Forest

In order to assess which algorithm would perform optimally for classifying mangrove extent, the Random Forest and $k$-NN algorithms were implemented and
used with a range of input variables. The algorithms were implemented using the SciKit-learn python module. The $k$-NN algorithm was run with $k$ values in 1–30 and the Random Forest classifier was run with a number of trees of 100, 250, 500, 1000–10000 (1000 intervals). The performance of each was assessed on the time taken to run the algorithm and by comparison of the output to that of the mangrove map of Giri et al. (2011). It is acknowledged that the dates of the current classification and that of Giri et al. (2011) are not coincident, yet a comparison between the two would reveal shortcomings in the algorithm if the variation between the two datasets was to be large.

The $k$-NN classifier did not perform as consistently as the Random Forests classifier and there was a large range in the percentage of mangrove classified that was in agreement with the map of Giri et al. (2011), although the maximum correlation was higher than that of Random Forests (Table 6.1). The processing time was also substantially larger than that of the Random Forests algorithm. The largest agreement with Giri et al. (2011) from the $k$-NN algorithm was often with a $k$ value of 2. This is an inappropriate value to use as an even value could potentially be prevented from being split into a majority. Further to this, a value which is a multiple of the number of classes (3) is also inappropriate to use. Agreement with the map of Giri et al. (2011) cannot be used as a measure of accuracy as the mangrove extent may have changed since the dates from which the map was derived.
Figure 6.9: The workflow of the refining of the mask used to extract training data for the machine learning algorithm. A probability map is generated from existing maps, training data is gathered, the mask is refined using a ML classifier, and the mask is grown towards the sea.
CHAPTER 6. MAPPING MANGROVE EXTENT

Table 6.1: Variation between $k$-NN mangrove map and that of Giri et al. (2011) for a varying value of $k$. Provided are the maximum and minimum percentage of agreement with Giri et al. (2011) and the difference between them.

<table>
<thead>
<tr>
<th>Location</th>
<th>Maximum(%)</th>
<th>$k$ value</th>
<th>Minimum(%)</th>
<th>$k$ value</th>
<th>Difference(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amapa State</td>
<td>84.76</td>
<td>2</td>
<td>76.46</td>
<td>29</td>
<td>8.3</td>
</tr>
<tr>
<td>Braganinha</td>
<td>80.53</td>
<td>2</td>
<td>77.27</td>
<td>29</td>
<td>3.25</td>
</tr>
<tr>
<td>Sao Luis</td>
<td>83.3</td>
<td>2</td>
<td>77.94</td>
<td>1</td>
<td>5.36</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>87.25</td>
<td>2</td>
<td>81.07</td>
<td>27</td>
<td>6.18</td>
</tr>
<tr>
<td>Guayaquil</td>
<td>83.28</td>
<td>2</td>
<td>81.79</td>
<td>1</td>
<td>1.49</td>
</tr>
<tr>
<td>French Guiana</td>
<td>69.43</td>
<td>2</td>
<td>60.34</td>
<td>29</td>
<td>9.09</td>
</tr>
<tr>
<td>Guinea Bissau</td>
<td>70.51</td>
<td>2</td>
<td>62.76</td>
<td>29</td>
<td>7.75</td>
</tr>
<tr>
<td>Honduras</td>
<td>70.38</td>
<td>2</td>
<td>65.24</td>
<td>21</td>
<td>5.14</td>
</tr>
<tr>
<td>Mozambique</td>
<td>41.03</td>
<td>2</td>
<td>24.77</td>
<td>29</td>
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</tr>
<tr>
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<td>2</td>
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</tr>
<tr>
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<td>71.25</td>
<td>1</td>
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</tr>
<tr>
<td>Perak</td>
<td>91.36</td>
<td>2</td>
<td>82.92</td>
<td>29</td>
<td>8.44</td>
</tr>
<tr>
<td>Niger Delta</td>
<td>89.71</td>
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<td>85.59</td>
<td>1</td>
<td>4.12</td>
</tr>
<tr>
<td>South Kalimantan</td>
<td>71.18</td>
<td>2</td>
<td>60.17</td>
<td>1</td>
<td>11.01</td>
</tr>
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<td>Kakadu</td>
<td>87.55</td>
<td>2</td>
<td>81.84</td>
<td>29</td>
<td>5.71</td>
</tr>
<tr>
<td>Venezuela</td>
<td>59</td>
<td>2</td>
<td>46.73</td>
<td>29</td>
<td>12.27</td>
</tr>
</tbody>
</table>

The out-of-bag score was calculated for each implementation of the Random Forest classifier, with a result greater than 0.99 for each. The out-of-bag score uses values not in the random sample used to build the decision tree to validate the accuracy of the result where a value nearer 1 is associated with increased accuracy. The maximum correlation with Giri et al. (2011) for each study site was not as high for that of the corresponding $k$-NN, yet the range of correlation values was small. This indicates an increased reliability of the algorithm as the result is not substantially affected by the number of decision trees, which subsequently provide the number of votes for an object belonging to a class. The outputs of the map were also manually verified to ensure that the lower correlation with Giri et al. (2011) was not indicative of a worse result than that of the $k$-nn or that a systematic error was the cause of the reduced correlation. A high correlation with the map of Giri et al. (2011) is not indicative of a higher classification accuracy, yet a larger range between the maximum and minimum correlation value indicates an increased sensitivity of the algorithm to the input parameters and training data. An example of this occurred in Mozambique, where the correlation between the $k$-
NN and map of [Giri et al., 2011] was low, even at its maximum. This was a result of inaccuracies in the map of [Giri et al., 2011] and not the poor performance of the algorithm. The difference between the maximum and minimum correlation percentages of the random forest algorithm with the map of [Giri et al., 2011] are presented in Table 6.2.

Table 6.2: Variation between Random Forest classified mangrove map and that of [Giri et al., 2011] for a varying number of trees. Provided are the maximum and minimum percentage of agreement with [Giri et al., 2011] and the difference between them.

<table>
<thead>
<tr>
<th>Location</th>
<th>Maximum(%)</th>
<th>n trees</th>
<th>Minimum(%)</th>
<th>n trees</th>
<th>Difference(%)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>100</td>
<td>78.89</td>
<td>5000</td>
<td>0.14</td>
</tr>
<tr>
<td>Bragantina</td>
<td>79.02</td>
<td>100</td>
<td>78.96</td>
<td>8000</td>
<td>0.06</td>
</tr>
<tr>
<td>Sao Luis</td>
<td>80.95</td>
<td>100</td>
<td>80.85</td>
<td>1000</td>
<td>0.1</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>86.02</td>
<td>250</td>
<td>85.85</td>
<td>7000</td>
<td>0.17</td>
</tr>
<tr>
<td>Guayaquil</td>
<td>82.85</td>
<td>100</td>
<td>82.77</td>
<td>250</td>
<td>0.08</td>
</tr>
<tr>
<td>French Guiana</td>
<td>64.43</td>
<td>100</td>
<td>64.28</td>
<td>3000</td>
<td>0.15</td>
</tr>
<tr>
<td>Guinea Bissau</td>
<td>65.77</td>
<td>100</td>
<td>65.62</td>
<td>1000</td>
<td>0.15</td>
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<tr>
<td>Honduras</td>
<td>67.49</td>
<td>100</td>
<td>67.37</td>
<td>1000</td>
<td>0.12</td>
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<tr>
<td>Mozambique</td>
<td>33.12</td>
<td>100</td>
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<td>83.62</td>
<td>100</td>
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<td>8000</td>
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<tr>
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<td>Niger Delta</td>
<td>87.41</td>
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<td>South Kalimantan</td>
<td>65.44</td>
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<td>750</td>
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<td>Venezuela</td>
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<td>49.74</td>
<td>500</td>
<td>0.26</td>
</tr>
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</table>

The Random Forest algorithm required less processing time than the $k$-NN classifier but processing time increased substantially with an increased number of trees. As the out-of-bag score was high ($>0.99$) for all number of trees, a trade-off was reached between ensuring a high enough number of trees were selected to ensure an accurate result whilst acknowledging the requirement for a suitable processing time. A value of 1000 trees was selected for each study site as this represented a large number of trees whilst the comparison between the result and the map of [Giri et al., 2011] was within 1 standard deviation of the mean of the combined results derived from all of the numbers of trees tested. This also enabled a large quantity of trees to be used without excessive compromises in
processing time. As the out-of-bag score was high for each implementation, the accuracy gained by increasing the number of trees beyond this could not justify the penalty in processing time. An increased number of trees is preferred as this enables the classifier to benefit from a greater number of votes on which to use to assign a data point to a class. This is beneficial as a greater number of trees is able to reduce potential ambiguity that may occur through the random selection of training data by ensuring sufficient trees are built in order to differentiate the classes. Although a fewer number than 1000 trees attained a larger correlation with that of the map of Giri et al. (2011) this correlation cannot be assumed as a direct indicator of accuracy, although the small variation between 100 and 10000 trees suggests that all results from a low to a high number of trees are robust. This was recognised by Clewley et al. (2014) in the classification of Alaskan wetlands, whereby the out-of-bag score did not markedly increase beyond 200 trees. It was, however, acknowledged that a larger number of trees is preferred, as was chosen in this current study, to enable the algorithm to benefit from a maximum number of class votes.

An extremely random forests algorithm, that randomly chooses splits at the tree nodes as opposed to the most discriminative, was also implemented. The results showed no additional benefit of using the Random Forest algorithm and so was not pursued as the algorithm for image classification.

6.1.4.2 Random Forests: coastal region of interest

Although the imagery was subset to eliminate an excessively large number of objects, when running the classification, only the objects that lie within a suitable habitat are of interest. Although a general relationship was described for the distribution of mangrove forests with distance from water and elevation, two individual study sites can differ so that they may not be able to both be adequately described by the same characteristics. Although for each individual study site mangrove trees are more frequent with increased proximity to water and at low elevations, the statistics from each study site are only a part of the global statistics and may not be defined by them. In order to adequately represent the
6.1. METHOD

relationship between mangrove forests and their environment, yet maintain applicability to each study site, the images were subset on thresholds derived from statistics that describe the distribution of mangrove within each study site. This prevents an excessive number of image objects being classified if the study site contained only fringes of mangrove within close proximity to the ocean or only mangroves of low height/elevation.

For each study site the distance from water for each object that contained the mangrove map of Giri et al. (2011) was read from the RAT. Due to anomalous values in the dataset the maximum value was not representative of the true maximum extent of the mangrove. To remedy this the 90th percentile distance from water was calculated and was doubled to ensure that all mangrove extent was included, accounting for that which may have advanced outside of the extent of Giri et al. (2011). Similarly, the elevation (SRTM height) of each object containing the extent of Giri et al. (2011) was read from the RAT. The 99th percentile of elevation was calculated and used as the maximum elevation threshold, unless this exceeded 50 m. An upper threshold of 50 m was selected through a combination of maximum mangrove height and tidal range. Mangrove height is commonly in the region of 20–30 m, occurring in rare instances as high as 40 m. The largest tidal range in the tropics is 7 m (Tidesandcurrents.noaa.gov, 2013) and so a conservative tidal range height of 10 m was selected. It is assumed that through a combination of these, the greatest elevation of a mangrove forest object would be no greater than 50 m.

6.1.4.3 Segmentation

The coastal region of interested was segmented using the segmentation algorithm of Shepherd et al. (2013) within RSGISLib. The parameters were kept the same as the segmentation for the Bayesian maximum–likelihood refinement of the training data mask (Section 6.2.3.5), where the minimum number of pixels per object was 4 and the number of seed clusters remained at 80. The segmentation was carried out on the HH and HV bands.
6.1.4.4 Sampling of training data

Although the imagery is subset to eliminate large numbers of objects the quantity of training data, especially for the ‘other’ non-mangrove class could be large. The reading and fitting of the training data by the algorithm is a computationally expensive process and so to provide the algorithm with the entirety of the training data would be inefficient. However, sub-sampling the training provides its own caveats in that there is a potential risk of not sampling the full range of the data, leading to the under-representation of the class distribution. A function within RSGISLib is able to sub-sample the distribution of data based upon its histogram. The user is able to define a percentage of the data to maintain and each histogram bin is sub sampled, creating a new dataset that is a proportion of the original dataset but with the same distribution in the feature space. A sub-sample of 75% of the training data for each study site was used as this provided the largest quantity of training data for the smallest loss in processing time and resources required. This is exemplified in Figure 6.10 and Figure 6.11 whereby the full training dataset is sub-sampled whilst maintaining the distribution.

6.1.4.5 Classification regions

A final processing step before the algorithm could be run defined the target objects that were to be classified. This assigned all of the objects within the coastal region of interest to be classified.

6.1.5 Accuracy assessment

The accuracy assessment was two-fold, composed of a combination of stratified random sampling and transects across class boundaries. A two-fold approach such as this provided a means of assessing not only the accuracy of the proportion of the image correctly classified but also provided a method of assessing the accuracy of the class boundaries as one class transitions into another. The accuracy of the classification is provided, with full error matrix and kappa statistics.
6.1. METHOD

Figure 6.10: Distribution of the whole training data for a class.

Figure 6.11: Sub-sample of the training data, maintaining the shape of the distribution.
CHAPTER 6. MAPPING MANGROVE EXTENT

6.1.5.1 Stratified random sampling

The initial accuracy assessment implemented the stratified random sampling of points across the available classes. This was done using RSGISLib to randomly create points from a raster file composed of the classes of interest. The classes of ‘Mangrove’, ‘Water’ and ‘Other’ were assessed in this study. Each point was then manually interrogated against high resolution optical data and a combination of the ALOS and Landsat images used in the classification method to assign whether a given point was correct or incorrect. In the instances where the class was incorrect the true class was noted, allowing a full error matrix to be constructed. The high resolution imagery used was that of Google Earth imagery which was available as a plug-in for the GIS software QGIS. This imagery was composed of a variety of datasets but was often available at a resolution of 1–2 m, although coarser Landsat (30 m) imagery was used where high resolution data was unavailable.

As the classification was carried out on medium resolution imagery (25–30 m) using image objects, comparing the accuracy of a single point against high resolution imagery could not provide a fair measure of accuracy. For example, small areas of bare ground between mangroves may be visible within high resolution imagery but would not be detected in the coarser imagery. A mangrove point falling within this region of bare ground would be incorrectly classified in comparison to the high resolution imagery but would be correctly classified in comparison to the ALOS and Landsat input imagery. To overcome this limitation, each point was buffered with a 50 m radius and the class assigned to the point was assessed within the context of the pixels within the buffer. This enabled consideration to be given for the difference in resolution of the classified imagery and the reference imagery.

To ensure that a sufficient accuracy assessment was conducted over large areas of classified imagery, a large number of points were manually assessed. Congalton and Green (2008) state that for maps less than 1 million hectares and with less than 12 classes, 50 points per class is an adequate sample size. Maps greater than
1 million hectares or with more than 12 classes should have 75 to 100 accuracy assessment points whilst ensuring statistical and practical validity. For each study site the proportion of mangrove in the scene and the classified area was considered when choosing the number of points. A minimum of 200 points per class (600 per study site) was chosen. The number of points for each class for all of the study locations in this study is provided in Table 6.3.

Table 6.3: The number of validation points per class and total per site used at each study location.

<table>
<thead>
<tr>
<th>Study Site</th>
<th>Points per Class</th>
<th>Points per Study Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amapa</td>
<td>250</td>
<td>750</td>
</tr>
<tr>
<td>Bragantina</td>
<td>250</td>
<td>750</td>
</tr>
<tr>
<td>Sao Luis</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Guayaquil</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>French Guiana</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Guinea Bissau</td>
<td>350</td>
<td>1050</td>
</tr>
<tr>
<td>Honduras</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Mozambique</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Sumatra</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Mahakam Delta</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>South Kalimantan</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Perak</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Niger Delta</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Kakadu</td>
<td>200</td>
<td>600</td>
</tr>
<tr>
<td>Venezuela</td>
<td>300</td>
<td>900</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>10050</strong></td>
</tr>
</tbody>
</table>

6.1.5.2 Transects

It is acknowledged that classification error is spatially correlated at the boundary between classes (Foody, 2002). This is especially the case where there is no discrete boundary between classes but where a classification has to form a boundary from continuous data (Congalton and Green, 2008). In this study this problem could potentially present itself on the landward margin of the mangrove class, whereby the mangrove class transitions to other vegetation. In instances whereby mangroves transition to tropical rainforest, a discrete boundary between the two classes is unlikely to exist, yet is required by the classification. Furthermore, even in cases where the class boundary is expected to be more defined,
such as the transition from mangrove to water, this is not always the case due to growth stages of mangrove and the position of tides. This, in some part, is also a product of the initial image segmentation and where the boundaries between image objects are formed. The number of validation points used within the transects at each study site is provided in Table 6.4.

Table 6.4: The number of validation points used in across-class boundary transects.

<table>
<thead>
<tr>
<th>Study Site</th>
<th>Points per Study Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amapa State</td>
<td>459</td>
</tr>
<tr>
<td>Braganina</td>
<td>371</td>
</tr>
<tr>
<td>Sao Luis</td>
<td>316</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>296</td>
</tr>
<tr>
<td>Guayaquil</td>
<td>273</td>
</tr>
<tr>
<td>French Guiana</td>
<td>436</td>
</tr>
<tr>
<td>Guinea Bissau</td>
<td>607</td>
</tr>
<tr>
<td>Honduras</td>
<td>331</td>
</tr>
<tr>
<td>Mozambique</td>
<td>271</td>
</tr>
<tr>
<td>Sumatra</td>
<td>301</td>
</tr>
<tr>
<td>Mahakam Delta</td>
<td>157</td>
</tr>
<tr>
<td>South Kalimantan</td>
<td>328</td>
</tr>
<tr>
<td>Perak</td>
<td>152</td>
</tr>
<tr>
<td>Niger Delta</td>
<td>290</td>
</tr>
<tr>
<td>Kakadu</td>
<td>167</td>
</tr>
<tr>
<td>Venezuela</td>
<td>272</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>5027</strong></td>
</tr>
</tbody>
</table>

In order to quantify this potential source of error, transects composed of points were constructed across class boundaries and each point was assigned the class derived from the corresponding object in the classification. The accuracy of the class was then assessed with reference to the input imagery and high resolution Google Earth imagery. Each point was buffered by 40 m as with the stratified random points and the land cover class was assessed as the proportion that occupied the polygon as opposed to at single point. The tangents were drawn in QGIS and RSGISLib was used to convert the polyline to points, with a user defined distance between points. As with the random stratified points, RSGISLib was used to assign a class to each point from the classified image. Each point was then compared with reference imagery within QGIS.
6.2 Results

6.2.1 2010 baseline classification

The method was able to achieve a classification for each of the study sites. The classification results are presented in Table 6.5. Displayed is the area of mangrove classified for each study site, the corresponding area for each study site mapped by Giri et al. (2011) alongside the difference between the two maps. The accuracy of each map is presented, including the accuracy of the stratified random points, the cross-border tangents, the combination of the two approaches and the kappa statistic. Examples of the classifications are provided with the full classification for each study site provided in Appendix A.1.

The difference between the area of mangrove mapped in this study and that mapped by Giri et al. (2011) was low overall (0.5%), although there were some large discrepancies in the mangrove area at individual study sites. The difference between the mangrove map of Giri et al. (2011) and this study was low (<10%) at the Bragantina coastline, Sao Luis (Brazil), French Guiana, Guinea Bissau, the Mahakam Delta (Kalimantan, Borneo) and Perak (Malaysia), despite a difference of between at least a decade in the imagery used. This, however, does not mean that the mangrove forest classified in both studies was the same extent and had not changed in the interim. The difference between the mangrove areas at French Guiana was 5%, yet the mangroves of the French Guiana coastline are dynamic. Although the area of mangroves is similar, the extent of the forest may have changed. Conversely, there was a large difference in the mangrove area at the study sites of Amapa State (Brazil, 29%), Todos os Santos (Brazil, 39%), Mozambique (41.9%), Kakadu National Park (Australia, 54.1%) and Venezuela (25%). The accuracies for the individual classification were high, with the lowest value being 85.1% (Mozambique) and the highest being 98.3% (Guayaquil, Ecuador). A full error matrix of a combination of the 16 study sites is provided in Table 6.6. The greatest sources of class confusion with the mangrove class were the classes of plantations, dryland forests and agriculture, with lesser confusion...
with savannah and riparian vegetation. This confusion with these classes, however, is small when the total number of correctly classified mangrove and water points is considered. This is reflected in the high overall accuracy (92.6%) and high kappa value of 0.89.

6.2.1.1 High accuracy

The mangroves of Guayaquil, Ecuador, were classified (Figure 6.12) with an accuracy of 98.3%, demonstrating that the mangrove in the region was classified with little overclassification or omission of mangrove. The mangrove extent classified had a well defined boundary and there was little class confusion between mangrove and other classes. This was due to the environment at Guayaquil, whereby the wet mangrove is surrounded by an arid landscape which creates a contrast that makes the definition of the mangrove boundary easy to classify. There is little other vegetation within the region that could cause potential class confusion, with the exception of an area of riparian vegetation which was adequately excluded from the mangrove training and satisfactorily classified as non-mangrove by the Random Forests algorithm. Within the mangrove forest, aquaculture ponds form geometric boundaries and form another contrast with the mangrove that is easily defined.
Table 6.5: Classification results and accuracy of classified mangrove at 16 locations across the tropics using the Random Forests algorithm.

<table>
<thead>
<tr>
<th>Study Site</th>
<th>Area (ha)</th>
<th>Giri Area (ha)</th>
<th>Giri Difference (%)</th>
<th>Stratified Random Accuracy (%)</th>
<th>Border Accuracy (%)</th>
<th>Overall Accuracy (%)</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amapa state</td>
<td>130870</td>
<td>92900</td>
<td>29</td>
<td>94</td>
<td>97.39</td>
<td>95.4</td>
<td>0.91</td>
</tr>
<tr>
<td>Bragantina</td>
<td>251420</td>
<td>234730</td>
<td>6.6</td>
<td>92</td>
<td>95.4</td>
<td>93.1</td>
<td>0.88</td>
</tr>
<tr>
<td>Sao Luis</td>
<td>172820</td>
<td>169670</td>
<td>1.8</td>
<td>92.8</td>
<td>90.2</td>
<td>90.1</td>
<td>0.89</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>55270</td>
<td>35920</td>
<td>35</td>
<td>89.8</td>
<td>71.8</td>
<td>86.1</td>
<td>0.85</td>
</tr>
<tr>
<td>Guayaquil</td>
<td>134130</td>
<td>152100</td>
<td>11.3</td>
<td>97.7</td>
<td>99.6</td>
<td>98.3</td>
<td>0.97</td>
</tr>
<tr>
<td>French Guiana</td>
<td>142100</td>
<td>150000</td>
<td>5.3</td>
<td>90.7</td>
<td>89.9</td>
<td>90.4</td>
<td>0.86</td>
</tr>
<tr>
<td>Guinea Bissau</td>
<td>592990</td>
<td>740430</td>
<td>19.9</td>
<td>93.9</td>
<td>91.8</td>
<td>93.7</td>
<td>0.91</td>
</tr>
<tr>
<td>Honduras</td>
<td>104030</td>
<td>89360</td>
<td>14.1</td>
<td>94.2</td>
<td>90</td>
<td>92.7</td>
<td>0.91</td>
</tr>
<tr>
<td>Mozambique</td>
<td>24230</td>
<td>41710</td>
<td>41.7</td>
<td>89.2</td>
<td>73.1</td>
<td>85.1</td>
<td>0.84</td>
</tr>
<tr>
<td>Sumatra</td>
<td>150570</td>
<td>111590</td>
<td>25.9</td>
<td>91.8</td>
<td>87.4</td>
<td>90.5</td>
<td>0.88</td>
</tr>
<tr>
<td>Mahakam Delta</td>
<td>69980</td>
<td>76980</td>
<td>9.1</td>
<td>92</td>
<td>98.1</td>
<td>93.3</td>
<td>0.88</td>
</tr>
<tr>
<td>South Kalimantan</td>
<td>58770</td>
<td>51250</td>
<td>12.8</td>
<td>91.2</td>
<td>89</td>
<td>90.5</td>
<td>0.93</td>
</tr>
<tr>
<td>Perak</td>
<td>44050</td>
<td>43930</td>
<td>0.3</td>
<td>95.3</td>
<td>98</td>
<td>95.9</td>
<td>0.94</td>
</tr>
<tr>
<td>Niger Delta</td>
<td>372440</td>
<td>317670</td>
<td>14.7</td>
<td>95.7</td>
<td>96.2</td>
<td>95.8</td>
<td>0.87</td>
</tr>
<tr>
<td>Kakadu</td>
<td>9800</td>
<td>21350</td>
<td>54.1</td>
<td>97.3</td>
<td>95.8</td>
<td>97</td>
<td>0.96</td>
</tr>
<tr>
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<td>288260</td>
<td>25</td>
<td>94</td>
<td>91.5</td>
<td>93.4</td>
<td>0.90</td>
</tr>
<tr>
<td><strong>Combined</strong></td>
<td><strong>2529760</strong></td>
<td><strong>2517850</strong></td>
<td><strong>0.5</strong></td>
<td><strong>93.3</strong></td>
<td><strong>91.2</strong></td>
<td><strong>93.3</strong></td>
<td><strong>0.90</strong></td>
</tr>
</tbody>
</table>
Table 6.6: Full error matrix for the combined classification results.

<table>
<thead>
<tr>
<th></th>
<th>Water</th>
<th>Mangrove</th>
<th>Other</th>
<th>Plantation</th>
<th>Dryland Forest</th>
<th>Savannah</th>
<th>Mudflat</th>
<th>RiparianVeg</th>
<th>Agriculture</th>
<th>User</th>
<th>User(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>4940</td>
<td>17</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4958</td>
<td>99.6</td>
</tr>
<tr>
<td>Mangrove</td>
<td>6</td>
<td>5179</td>
<td>17</td>
<td>94</td>
<td>505</td>
<td>60</td>
<td>2</td>
<td>34</td>
<td>118</td>
<td>6015</td>
<td>86.1</td>
</tr>
<tr>
<td>Other</td>
<td>16</td>
<td>282</td>
<td>4375</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>4674</td>
<td>93.6</td>
</tr>
<tr>
<td>Plantation</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dryland Forest</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Savannah</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mudflat</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>RiparianVeg</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Agriculture</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Producer</td>
<td>4962</td>
<td>5478</td>
<td>4392</td>
<td>94</td>
<td>506</td>
<td>60</td>
<td>2</td>
<td>34</td>
<td>119</td>
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<td>Producer (%)</td>
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<td>99.6</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>92.6</td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.89</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Whilst the environment is, therefore, conducive to attaining accurate results the classification algorithm performs well in separating the forest from the surrounding classes. This is not solely achieved through the classification algorithm but also reflects the performance of the segmentation to adequately define the boundaries between classes. The contrast between the wetlands of the mangrove forests and the dry surrounding land was adequately captured within the training data, demonstrating the high quality and accuracy of the training data derived from the \textit{a priori} dataset. The classification of the mangroves of Guayaquil are an example of the holistic method attaining good results with each component performing to a high standard. The difference in mangrove area between \cite{Giri2011} and this work was 11.3\%, with respective mangrove areas of 152,110 ha and 134,140 ha, despite an prominent area of mangrove classified in this work through an advance in mangrove in the region. The larger extent of \cite{Giri2011} is not attributed to large differences in the maps but the culmination of subtle differences. This work generate a map whereby the mangrove boundary with the water in the scene is a pixel smaller around the edge of the mangrove than defined by \cite{Giri2011} (Figure 6.13). The culmination of this difference for every mangrove border in the scene adds to a large difference between the maps of 17970 ha. Other differences in the maps are accounted for by the temporal difference between the imagery used, with each map containing areas of mangrove not contained in the other due to changes in the forest extent.
Figure 6.12: Classification of Mangroves at Guayaquil, Ecuador.
Figure 6.13: The difference in the classification of Giri et al. (2011) (blue) and this study (green) can be seen by a greater extent of mangrove by Giri et al. (2011) in places with an additional pixel of mangrove around the edge of the classification derived from this study. This is accountable for the greater area of mangrove classified by Giri et al. (2011) at Guayaquil, Ecuador.
6.2.1.2 Improvement to Giri et al. (2011)

The map of Giri et al. (2011) utilised imagery that was in excess of a decade old at the date of publication and was inhibited by cloud cover in places. This caused the mangrove extent to be excluded or poorly classified in regions. An example of this is at Riau, Sumatra (Figure 6.14) where the mangrove is poorly classified along the coast and misclassified inland. The combination of radar with composite mosaic optical imagery, was able to resolve this limitation.

Despite no training data being collected for the southern portion of the region, the mangrove was successfully classified with additional mangrove fringes being classified along the coast and inland along the banks of rivers where brackish water permitted, to an extent of no more than 5 km. This is a substantial improvement to the map of Giri et al. (2011) and demonstrates the ability of the method to generate a global mangrove map over the tropics where cloud cover inhibits the use of optical imagery. The total mangrove area was 25.9\% larger than that classified by Giri et al. (2011), with this study classifying a greater quantity of mangrove on the landward margin of the mangrove. Although the landward margin encroaches onto plantations which have spectral and backscatter values similar to mangrove, the mangrove was classified with an accuracy of 90.5\% and so cannot be attributed to classification error. A portion of this gain, can be attributed to the improvement in classification and the temporal difference between the datasets as the mangrove in the region has advanced in a seaward direction since the map of Giri et al. (2011).
Figure 6.14: A) Existing mangrove extent of Giri et al. (2011) with missing/erroneously classified mangrove in the southern portion of the region, interpreted as a consequence of cloud cover. B) An improvement over the existing map by the accurate classification of mangrove in the southern portion of the region.
Conversely, the diversity of the study sites revealed limitations of the method and instances where mangrove was erroneously classified. This resulted in the overclassification of mangroves in some regions and the exclusion of mangroves in others.

### 6.2.1.3 Training data

The high accuracy of the results is dependent, in part, upon the quality of the training data. This demonstrates that the mask derived from the *a priori* dataset from which training data was collected was adequately improved by the Bayesian maximum-likelihood classification. The classifier was able to remove erroneous classes from the mangrove class, in order to ensure only mangrove training data was collected using the mask. This is exemplified in Figure 6.15 whereby the Bayesian maximum-likelihood classifier reclassifies non-mangrove land cover types at Riau, Sumatra, that were included in the *a priori* mangrove extent. These errors occurred as a consequence of the temporal difference between the data from which the mask was generated and the current land cover types. This demonstrated that the pre-processing of this dataset was warranted to ensure that mangrove training data was accurately collected and performed to a high standard. The omission of this step would have introduced error into the reclassification of the mangrove extent by the machine learning algorithm.
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Figure 6.15: A) The results of the Bayesian maximum-likelihood classifier within the existing extent of the a priori mask. The red circles highlight objects that have been reclassified as non-mangrove. B) A colour composite Hansen et al. (2013) Landsat scene. The red circles correspond to regions that have been reclassified by the Bayesian maximum-likelihood classifier, demonstrating that the land cover type has been correctly reclassified as non-mangrove.
6.2.1.4 Context

The difference between the mangrove area classified at Amapa state in this study and that classified by Giri et al. (2011) was 37990 ha, equitable to a 29% difference. The cause of this was a larger classification of mangrove area at the study site in numerous places. This study classified a large number of isolated patches of mangrove that were not present in the map of Giri et al. (2011). These were erroneously classified as they were not within close proximity to saline/brackish water and were separated from other mangrove forests in the region which either grow in continuous forest blocks or in fringes along the coast. The cause of this misclassification was due to the similar spectral and backscatter values of the mangrove and non-mangrove class which could not be distinguished from one another by the Random Forests algorithm. The isolated forest blocks require further rules that govern their location within the context of their environment to separate them as incorrectly classified mangrove. Applying rules that relate to the area would be inappropriate at a global level as some mangroves occur in small fringes or are fragmented into small blocks by anthropogenic activity whilst rules that govern their distance from water have already been applied on a scene by scene basis for the definition of the region of interest for the Random Forests algorithm. These incorrectly classified mangrove can be seen in Figure 6.16.

6.2.1.5 Mangrove omission

The mangroves of the Mahakam Delta, Kalimantan, are heavily fragmented by historic aquaculture in the region, resulting in the removal of a large quantity of mangrove from the area for shrimp ponds. The ponds are separated by a channel that drains them which is flanked by fine fringes of mangrove. The fine fringes are not classified within this study and they are assigned to the ‘other’ class. A potential cause of this could be due to radar scattering from these areas. The influence of the water could reduce the backscatter below that typical of the mangrove class yet not low enough to enable them to be classified as water. This is exacerbated by mangrove canopies that overhang channels and cause a backscatter and spectral pixel value composed of both land cover types.
Figure 6.16: Pockets of mangrove classified inland from the coast and isolated from other mangrove are interpreted as being a consequence of the similarity in NDWI of these regions with the mangrove class.
Conversely, some had much increased backscatter, interpreted as the consequence of enhanced double-bounce scattering from the flat water surface and vertical mangrove. Although some pixel values were the same as that of the larger areas of mangrove forest in the region, the average values of the image objects were not consistent with those of the mangrove class. The fringe mangroves and water channels are captured within 2 pixels of the PALSAR imagery and each pixel contains information from two distinct land cover classes, deriving a pixel value that is not representative of either class. These channels are subsequently not classified as mangrove (Figure 6.17).

These regions are small yet contributed to 9.1% less mangrove classified in this work than by Giri et al. (2011), with 69980 ha classified in comparison to 76980. The majority of the difference at this study site, however, was due to the temporal difference in imagery between the studies, with less mangrove in this study due to the continued removal of mangrove for aquaculture in the region. As these areas form only a part of this difference, they were rarely represented in the accuracy assessment and the classification was able to maintain an accuracy of 93.3%.

6.2.1.6 Class confusion

A cause of reduced accuracy at some locations was the over classification of mangroves due to class confusion between mangroves and other vegetation species. This was prominent in Mozambique where tropical forest vegetation and the mangrove were confused with one another. This was a consequence of the spectral and backscatter values of the input images and not a failing of the method. Furthermore, this region was poorly mapped by Giri et al. (2011) whose map is refined to create training data for this work. The Bayesian maximum-likelihood method in this instance was unable to correct the existing map and separate the mangrove from the forest vegetation using radar backscatter and NDWI and NDVI indices, due to the similarity in their structure and reflectance characteristics. All vegetation cover in the tropics has a high NDVI value and this indice is used optimally when separating vegetation from non-vegetation classes. The separability of mangrove from non-mangrove classes can be achieved through the
6.2. RESULTS

Figure 6.17: Fringes of mangrove separated by water channels are omitted from the classification due to the combination of the classes providing different backscatter and reflectance values to the mangrove class. The fringes are also adversely affected by the mmu of the segmentation (1 ha) which would include pixels of both mangrove and surrounding aquaculture ponds.
use of NDWI, when the mangrove wetlands are readily discernible from dry non-
mangrove area. Within the tropics non-mangrove classes can have similar NDWI
values to the mangrove if high rates of rainfall are received. The small difference
between the extents reinforces that the misclassification was introduced by the
training data.

The inability of the refinement of the *a priori* dataset to separate these classes
introduced erroneous training data into the Random Forests algorithm. This
resulted in a difference in the two mangrove maps of 17480 ha (41.7%), although
this is interpreted to be caused by the inaccuracy of the map of Giri et al. [2011]
as this work yielded an accuracy of 85.1%. This was also evident at Sao Luis,
Brazil, where the mangrove was confused with other woody tropical vegetation.
In this instance areas of inaccurate training data derived from the *a priori*
dataset (Figure 6.18), combined with the wet environment on the eastern coast of Brazil
and the similar structure of the two vegetation classes restricted the separation
of the classes by the Random Forests algorithm. This led to an overclassification
of mangrove and loss of detail in the mangrove boundaries. The cause of the
error in the existing map is interpreted to be due to cloud cover. The method
implemented in this study does not suffer this limitation. The accuracy of the
classification was 90.1% with a total difference in mangrove area between this
product and the existing map of 1.8%.

### 6.2.1.7 Segmentation

The accuracy of the algorithm relies heavily upon the performance of the segmen-
tation algorithm. The ability of the segmentation to form objects of homogeneous
pixels and separate groups of heterogeneous pixels controls the statistical values
(mean/minimum/maximum) that are populated into the RAT. This, in turn,
defines the training data that is applied to the classification algorithm.

A noticeable feature at a number of study sites was the overclassification of nar-
row river channels between the mangrove as mangrove forest. This was a conse-
quence of the segmentation algorithm being unable to separate the channel from
the mangrove forest. This was exacerbated by the river channel often being cov-
Figure 6.18: Class confusion is caused by the similarity in training data between the mangrove and the non-mangrove classes collected by the *a priori* dataset. The red circles are over regions with NDWI values that are similar to the NDWI values of non-mangrove classes inland.
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erased in some part by a mangrove forest that fragments the river channel into smaller intermittent blocks of low backscatter and spectral values. Despite this the segmentation algorithm was applied with a minimum object threshold of four pixels to ensure that fine areas of mangrove were adequately segmented and so should have separated the water and the mangrove. This was noticeable at the Gulf of Fonesca (Honduras) and the Niger Delta (Nigeria) whereby narrow channels between the mangrove forests were included within the mangrove class. This contributed to the larger mangrove extent classified in this work than that of the existing mangrove baseline, of 14670 ha (14.1%) and 54770 (14.7%), respectively. The application of a post processing step after the classification to eliminate objects of low spectral values would not be sufficient here as the water pixels are often included in small quantities within an object where the majority of pixels are mangrove pixels, thus containing statistics that describe a mangrove object (Figure 6.19). Lowering the minimum object size of the segmentation would be inappropriate as this would direct the method closer to a pixel based approach which would contain more noise than an object oriented approach and could markedly increase the number of image objects and processing time. Despite this the classification accuracies remained high for the Gulf of Fonesca (92.7%) and the Niger Delta (95.8%).

6.2.1.8 Input image quality

A cause of classification error was introduced by the Landsat composite mosaic. As the composite is made up of multiple scenes, exacerbated by the scan line error of Landsat 7 ETM+, variation in environmental conditions at the time of image acquisition can cause a heterogeneous landscape when the image is mosaicked into a single scene. The NDWI is particularly prone to this where the NDVI remains more stable for a wide variety of tropical vegetation. The NDWI is susceptible to changes in soil and vegetation moisture, which is dependant upon changes in the local weather. An example of this occurred in Nigeria where the striping effect of the mosaic caused lines of mangrove to be classified that would not have occurred naturally (Figure 6.20). This effect was exacerbated in regions that were
Figure 6.19: The inability of the segmentation to adequately form objects of homogeneous pixels introduces error into the classification, through the subsequent population of the object with a mean value that is not representative of a single land cover type. This is highlighted in the red and blue circles whereby, an object contains both water and mangrove pixels, despite being above the mmu of 4 pixels.
heavily affected by cloud cover as these would need to be be composed of more
than one image in a greater number of places, forming a patchwork image that
could be heterogeneous and of poor quality for deriving training data. Despite
this, the error introduced by the input imagery must be accepted as a trade-
off against constructing new composite images, that would be susceptible to the
same limitations.

6.2.1.9 Registration

Correctly registered imagery is fundamental when relying upon data derived from
multiple scenes and from multiple modes. The accuracy of the product derived
from this work relies heavily upon the registration between the ALOS PALSAR
and the Landsat mosaic. This is particularly important at the boundary between
classes, where a sharp contrast between two or more classes could cause erroneous
training data if the object contains pixels of a single class in one image and pixels
of multiple classes in another due to registration error. Poor image registration
was evident, in some part, in all of the study site mosaics and required that the
Landsat mosaic at the Mahakam Delta, Kalimantan, was manually registered to
the ALOS PALSAR imagery, such was the magnitude of the registration error.
This was exemplified at Kakadu National Park, whereby registration error be-
tween the radar and optical imagery caused additional mangrove to be classified
in objects that contained water pixels (Figure 6.21). The Landsat composite im-
agery was well registered to other Landsat imagery and it is the ALOS PALSAR
scenes that are interpreted as being poorly registered. Radar imagery form the
basis of this work and is supplemented by optical imagery and thus the segmen-
tation was carried out on the radar data. A potential solution to this limitation
would be to segment the radar and optical imagery together which would prevent
objects formed in one mode of data containing multiple classes in another mode.
A more direct solution would be to ensure that the scenes are co-registered as
part of the pre-processing stage, although this would create a vast quantity of
additional time consuming processing, especially at the global level.
Figure 6.20: Striping in the colour composite imagery as a consequence of the merging of a number of Landsat images collected at different dates causes heterogeneity in the surface reflectance of land cover types. This is evident at the Niger Delta whereby the scan line error of Landsat 7 ETM+ causes striping in the composite imagery.
Figure 6.21: The registration error between the ALOS PALSAR (Blue) and Landsat NDVI (Green) and NDWI (Red) indices at Kakadu National Park, Australia.
6.3 Discussion

Mangrove extent was successfully classified across all of the study sites representing a number of various environmental settings and range of mangrove forest types. This included large continuous expanses of mangrove such as the forests of the Bragantina coastline of Brazil, to the tightly constrained mangrove fringes of Kakadu National Park in Australia. Some of these mangroves border other tropical vegetation whilst others form large continuous stands that have a clear coherent boundary between other land cover types. The approach has demonstrated that it has global applicability and can be applied to mangrove environments across the tropics. Furthermore, the approach is able to do this over large study sites that include the entire coastline of countries, such as the coastlines of French Guiana and Guinea Bissau. Relative to the large areas that can be classified the mangrove is mapped with a high resolution using 25 m input data.

This was achieved using a geographic object-based image analysis (GEOBIA) approach implemented through an exclusively free and open source suite of software. Each stage of the method, from the pre-processing of the data through to classification and accuracy assessment was carried out using free and open source software. This approach, outlined in full by [Clewley et al. 2014], provides a complete workflow for mapping land cover using remotely sensed imagery. This guarantees that the approach is scalable and is applicable to both small expanses of mangrove through to continent scales and larger. The use of open source software relieves the approach from a dependence on software licenses and enables it to be fully customisable. The is also scalable in that it can be applied to a single study site or can be run simultaneously in a high performance computing environment to map large areas efficiently. The performance of the method was demonstrated through the accomplishment of accuracies greater than 90% across a combined mangrove area in excess of 2,500,000 ha.

The use of geographic object based image analysis (GEOBIA) for mangrove mapping has not been explored widely for mangrove mapping and is poorly repre-
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presented in the literature (Conchedda et al., 2008). GEOBIA is a recent development in the field of remote sensing and is not yet an established method for mapping mangrove extent.

The use of GEOBIA was used in this current study as image objects are able to reduce the granularity associated with per-pixel classifications, that are often exacerbated by radar imagery which are prone to speckle and a greater contrast between adjacent pixels than optical imagery, providing a grainy image (Nascimento et al., 2013). Furthermore, the mapping of mangroves are suited to object oriented approaches as they form discrete units that are continuous in cover, with relatively homogeneous canopies that commonly occur in zones parallel to coastal margins (Nascimento et al., 2013). The use of image objects, derived through the segmentation of the imagery, was able to represent the semantic information that could not be readily retrieved from a per-pixel approach and utilised the context of the image objects in relation to their neighbouring objects (Kamal and Phinn, 2011). This was particularly useful for defining the coastal area in which the Random Forests algorithm was run, through the use of elevation and distance of objects from one another that provided the mangroves with context within the environment. This enabled more control over the classification of image objects as image objects could be treated differently to one another based on their context rather than equally as would be required by per-pixel classifications. Furthermore, image objects provide the opportunity to utilise a 'trial and error' approach to qualitatively refine a classification to achieve the best result (Myint et al., 2008; Nascimento et al., 2013). The use of GEOBIA was fundamental in enabling the classification to achieve accuracies in excess of 90% and have commonly been demonstrated to out-perform per-pixel classifications (Kamal and Phinn, 2011; Myint et al., 2008) and has been demonstrated to be capable of classifying mangrove species within radar imagery with moderate accuracy (68.4%) (Flores De Santiago et al., 2013). These accuracies were derived from data that were included in this current study (e.g. ALOS PALSAR, Landsat) which are commonly achieved using much higher spatial resolution imagery (Heumann, 2011).
The aim of the chapter was to update the existing mangrove baseline across the tropics at high resolution. The method was designed to have the additional benefits of achieving products with a greater accuracy than that currently available using an approach that could be repeated if required, without requiring expendable resources.

There is one mangrove specific global map currently available, produced by Giri et al. (2011). This was achieved through the classification of over 1000 Landsat scenes acquired over the nominal years 1997–2000, using a hybrid supervised and unsupervised approach. This was achieved through the unsupervised k-means classifying of Landsat scenes and the manual selection of the mangrove classes. This method is believed to offer a number of advantages over the existing method. Firstly, this method was able to utilise data acquired closer to the date of the production of the map, limiting the difference between the map and the present state of the world’s mangroves. Secondly, this work utilised radar imagery and composite optical imagery, eliminating the potential for gaps in the map due to cloud cover and demonstrated this advantage by classifying additional mangrove than that of Giri et al. (2011) that was inhibited by cloud. The method used by Giri et al. (2011) was not a fully automated approach and required a large number of personnel for the manual selection of mangrove classes determined from the k-means classifier. The data processing at each stage of this workflow was automated with the exception of the requirement to gather training data. This approach could be fully automated by removing the Bayesian maximum-likelihood classification step to define the a priori dataset and by replacing it with a refinement that relies upon an implementation of the change detection method in Chapter 7. This would enable a completely automated method to be implemented. Although this work has not produced a global map, the accuracies attained for the classification of mangrove across large areas distributed globally were consistently greater than 90% in comparison to the qualitative assessment provided by Giri et al. (2011).
Other available global mangrove maps have limitations whilst do not do offer any additional benefits over this work. The map of Spalding et al. (1997) used aerial photography, optical Landsat and NOAA-AVHRR satellite imagery and ERS radar satellite imagery, to facilitate a manual interpretation and to fill gaps from maps derived from field maps and government inventories. This work is difficult to reproduce and requires a lot of manual intervention that cannot be automated. Updates to this map were made by the UN WCMC (Spalding, 2010), yet this did not create a global automated method but used Landsat data to improve and update the oldest data within the map of Spalding et al. (1997), using unsupervised classification algorithms.

The Random Forests classifier was able to classify mangrove forest extent with the high accuracies that have been previously observed with the algorithm (Mellor et al., 2013). The algorithm was able to adequately and accurately classify mangrove extent and differentiate it from other land cover classes at a variety of locations, with no modification of the training parameters required. This utilised one of the primary benefits of Random Forests of being able to be used with a small number of easily defined parameters (Pal, 2005) in comparison with other machine learning algorithms (i.e. SVMs) whilst achieving greater accuracies (Fernández-Delgado et al., 2014). The use of the Random Forest algorithm was appropriate given that the training data was contained a small number of classes composed of a number of sub-classes. The mangrove class contained mangrove of different growth stages and species whilst the ‘other’ class was composed of a large number of classes with a broad range of spectral and backscatter pixel values. This enabled classes that were not of interest to be collected as a single training dataset as the distribution of the data did not need to be defined (Breiman, 2001). This markedly improved the efficiency of the collection of training data for the classifier.

Random Forests and ensemble trees have not been used extensively for mangrove mapping with few examples available in the literature, but have been demonstrated to be capable of achieving classification accuracies of 84% (Simard et al.,
6.3. DISCUSSION

Other uses of decision trees have used ancillary GIS data alongside Landsat imagery for mapping mangroves attaining accuracies in excess of 80% (Liu et al., 2008; Clewley et al., 2015). The mangrove extent of Giri et al. (2011) could be used directly in the Random Forests algorithm in this work instead of being used to gather training data, but requires that the ancillary data is accurate to avoid introducing error into the classifier. The use of the existing mangrove extent may weight the classifier too heavily so that mangrove outside of the existing extent may be unclassified. The existing ancillary data is, therefore, better used within this study to collect training data than as a direct input into the classifier.

The combination of optical and radar data enabled high accuracies to be achieved as the different modalities were able to complement one another and provide different information. Optical data was able to provide information on the chemical and biophysical composition of the land cover classes whilst radar data provided information on their structure. This has been observed to aid mangrove classification, especially in the tropics where cloud, smoke and haze may require that radar is used in combination with optical data when it is inhibited by atmospheric conditions (Souza Filho et al., 2006). This present study was able to avoid this limitation of optical data by using a composite image, although these commonly represent data gathered from a number of years and do not represent a single point in time. Furthermore the use of radar data has been observed to enhance the mapping of mangrove vegetation due to the enhanced backscatter from double bounce scattering in inundated mangrove environments (Souza Filho and Paradella, 2002). The advantages offered by both datasets were capable of attaining greater accuracies than could be attained from the use of one dataset alone. This has been previously observed to yield an increase in accuracy in excess of 20% by using a combination of optical and radar datasets than using them independently (Held et al., 2003; Ramsey III et al., 1998). Fusing data of different modalities has been demonstrated to improve accuracy, although the combination of optical and SAR has received little attention for mangrove mapping, especially at large scales. Nevertheless, this has been previously achieved over large areas with an accuracy of 93.91%, and attained estimates of height, biomass and carbon
Similarly, Fatoyinbo and Simard (2013) used a combination of ICESat/GLAS and SRTM data to map the mangroves across the whole of Africa achieving an accuracy of 83%. The total area of mangrove mapped was comparable to this work, with 2,596,000 ha of mangrove mapped in comparison to 2,529,760 ha mapped within this study. Many other studies (Hashim et al., 1999; Cornforth et al., 2013; Kumar and Patnaik, 2013; Rao et al., 1999; Lucas et al., 2007) that utilise a combination of radar data with optical data or another radar dataset do not provide quantitative assessments of accuracy. This reflects the lack of data available in this field for conducting rigorous accuracy assessments of mangroves over large areas. This work, unlike these, was able to provide a thorough accuracy assessment that combined both class accuracy and across-class-boundary accuracy.

6.4 Conclusion

This study demonstrated the capability of a combination of remotely sensed data for mapping mangrove extent using a Machine Learning classifier within a GEOBIA approach for a number of study sites across the tropics. Mangrove extent was classified using a combination of optical and radar data at 16 study locations across the tropics. The total mangrove area classified was in excess of 2,500,000 ha and included mangroves from a diverse and broad range of environments ranging from continuous homogeneous forest to mangrove fringes. The classification attained high accuracies (>%) and was able to improve on the existing mangrove baseline. Despite this, limitations were provided by the registration error, between datasets, the performance of the segmentation algorithm and quality of the input data. These would need to be addressed in order to create a fully global product.

6.4.0.1 Future recommendations

Although high accuracies were attained, in order to achieve a complete global product, the following recommendations must be considered:

Image Registration To ensure that small features such as narrow channels are
classified accurately it must be ensured that the registration error between the radar and the optical datasets is minimised. This could be achieved during the pre-processing stage and would increase the accuracy of the product at the expense of additional, potentially labour intensive, processing.

**Improved Segmentation** The segmentation used performed well and was capable of segregating mangrove from other land cover types with adequate detail to enable the classifier to achieve high accuracies. Despite this, the segmentation does not perform as well in complex environments such as fine mangrove fringes and the transition between similar land cover types.

**Land Cover Differentiation** The largest error within the classification is the confusion between land cover types that cannot be segregated by the segmentation or their pixel values. A possible solution to this could be the use of additional data. This could be provided by C-band radar which has been demonstrated to segregate mangrove from other forested land cover types (Simard et al., 2002). Such data has recently been made available by ESA’s Sentinel-1 sensor.
Chapter 7

Detecting Change in Mangrove Extent

This chapter presents the description and application of a novel change detection method for monitoring mangrove forest extent. This is achieved using both ALOS PALSAR and JERS-1 radar imagery over a temporal range from 1 to 14 years. The benefits of the approach over existing change detection techniques are discussed.

7.1 Method

The approaches reviewed above are focused upon detecting changes in images whereby they conform to the two classes of ‘change’ or ‘no change’. This is done under the assumption that no description of the spatial information is available on the land cover classes in the scene and with no knowledge of the changes that may occur in those classes. This requires that differences in image pixels/objects are sought in order to assess change over a whole scene with no interest in the dynamics of a specific class. These approaches are unable to meet the requirements of a monitoring system that seeks the changes within specific classes. This information would enable the change to be measurable whilst simultaneously describing the nature of the change. In this study, the primary interest is around a single land cover class, with a secondary interest on the classes that it changes
to/from which cannot be retrieved using existing methods of change detection between SAR images. Furthermore, this work seeks a method whereby change is detected over a 14-year period between different sensors. This is a limitation of the existing methods which can only achieve this through a map-to-map approach. Current methods of change detection fail to meet these requirements and thus a new method of map-to-image change detection is proposed.

### 7.1.1 Map-to-image concept

The spatial extents of the classes of interest are known and it is therefore proposed that change features can be differentiated from the class using the distribution of the pixel/object values that are contained within the extent of the class of interest. The distribution extracted would be expected to be normal with deviations away from this identified as change features. An example of this would be a mangrove extent classified in 2010 imagery and used as a mask to extract the pixel/object values from a 2015 image. This would derive a normal distribution with any changes, such as the installation of aquaculture, to form an elongated tail.

The values could be extracted from any input image but is dependent upon a number of fundamental assumptions. Firstly, it assumes that the class values are normally distributed and that, secondly, the object values of the class and the change features are separable and are not both wholly contained within one normal distribution. This assumes that the majority of values that represent the class will be close to the median of the dataset and the values that represent the change will be far from the median. The third assumption is that the change features make up a proportionately smaller component of the class than the unchanged pixel values, so that the minority change values are sought within the normal distribution of the majority class values. This is exemplified in Figure 7.1.

It is assumed that the change features within the class distribution are within the tails and are not near the median, where the majority of the non-change pixel values will be clustered. In order to differentiate the change pixels from the majority class pixels a threshold needs to be found that optimally separates
the two. Ban and Yousif (2012) noted that in supervised change detection, the probability density functions of the change and non-change classes are known in advance. This is only partly true for this study as the distributions of the classes are known but are combined in a single distribution. Desclée et al. (2006) used the mean and standard deviation of the class statistics in order to threshold change from no change, yet this cannot be used in this study as the distribution of each class is different and the number of standard deviations from the mean will be different for each. This is also dependant upon the quantities of change and no-change pixels, which will affect the statistics of the distribution.

In order to overcome the limitation of hard thresholds, a method is required that is sensitive to the statistics of the class distribution and is able to vary the threshold for each class at each study site. As one of the fundamental assumptions is that the class is normally distributed with change features located in an elongated/populated tail away from the class median, it is assumed that a class with no change objects will be perfectly normally distributed. The difference between a distribution with change objects and one without change objects will be the normality of the class distribution. The removal of the change objects will normalise the class distribution, therefore, iteratively removing the tail of a distribution in increments from the tail-end towards the median until the distribution is normal, will separate the change from the non-change objects.

To do this an iterative approach was implemented whereby the normality of the distribution was calculated based upon measures of skewness and kurtosis. If the data was found to be non-normally distributed the tail of the distribution was removed over a user defined range using a user defined increment. This was done iteratively, recording measures of skewness and kurtosis. The combination of the lowest skewness and kurtosis values were used to identify the iteration at which the distribution was most normal. This value was then chosen as the threshold. This process is shown in Figure 7.2.
Figure 7.1: Extraction of image values using a map-to-image technique of change detection. A class mask (2010 Classification) is used to extract the values from an independent image (1996 JERS-1). These values form a distribution for the extracted class (mangrove) whereby the unchanged mangrove pixels are represented by the normal distribution and the change pixels, which have a pixel value outside of the distribution, are represented by the tail of the class distribution (blue region). The tail of the distribution is iteratively removed using a defined step and the normality of the distribution is tested at each iteration. The distribution and tail are separated when the distribution is most normal and the pixel values within the tail are highlighted as potential change features.
7.1.2 Datasets

ALOS PALSAR imagery was acquired for the years 2007–2010, with the latest scene used in the classification of mangrove extent. Additional JERS-1 scenes were also acquired for 1996, enabling changes in mangrove extent to be mapped over a broader temporal range. Although it is not required that the imagery used for detecting change has the same properties as that from which the classification was derived, the two datasets are both L-band SAR imagery at 25 m pixel resolution, covering a region of $1^\circ \times 1^\circ$. This limits the preprocessing required as the image extent and properties (pixel resolution) are the same, despite the scenes being independent.

7.1.3 Image preparation

To implement change detection between two years using image objects required a segmentation that was able to represent both images. To achieve this, separate segmentations were generated for each image and the intersection of the image objects was generated using the segmentation algorithm of Shepherd et al. (2013) and RSGISLib. This created a new segmentation that represented common segments in the independent segmentations. The resultant segments were then populated with the power data of the two years of interest and converted to dB. Initially this was done for the years 2007 and 2010. The segments were then populated with the 2010 baseline mangrove and water classes as binary masks using the mode value for each object. This enabled the proportion of each class within an image object to be used to decide whether to assign that object to a given class. This would enable objects containing a majority or minority of a class to be assigned appropriately.

7.1.4 Application to ALOS PALSAR time-series change detection

The automated detection of change from ALOS PALSAR imagery using object values was unable to separate change from no-change objects. This was due to
Figure 7.2: The variation in combined skewness and kurtosis with the sub-sampling of the distribution at varying points in the distribution tail. b) demonstrates the lowest combined skewness and kurtosis value over a) or c) and is used to select the threshold to separate change (distribution) from non-change (tail) features.
the narrow class distribution that was derived from the ALOS PALSAR imagery combined with the change features typically composing <1% of the objects between consecutive ALOS years. Small annual changes did not contribute to a large tail but deviated only slightly from the class distribution, so that the tail was below the sampling size over which the distribution was subset and tested for normality and skewness. The approach was therefore unable to separate the very small tail from the class distribution. To enhance the separability of the change features from the distribution, the object values were normalised using an image-to-image technique.

Detecting change between images acquired from the same satellite enabled standardised image-to-image methods to be utilised, on the assumption that the data acquired over multiple years was consistent. This was true for ALOS PALSAR data whereby the consistency in backscatter between years was noted to be good during the generation of the JAXA global forest/non-forest map (Shimada et al., 2014). Image ratioing was chosen as the image-to-image technique due to its simplicity over other more complex change detection techniques. This image ratioing was applied to the whole scene but change detection was carried out on one class at a time. This combined an image-to-image technique within a map-to-image approach that could be implemented repeatedly for an archive of imagery sourced from the same sensor.

The ratio between the two dates for each object was calculated for each class. As the changes between the mangrove and water class were between one another, the ratio equation was modified for each class. In order to detect changes within the mangrove class the more recent imagery was divided by the older imagery, whilst this was reversed in order to detect changes in the water class. The ratio values were written to the RAT and a threshold was used to differentiate change from non-change objects, per class. The ratio threshold chosen for each class was 2.5. This value was chosen through the manual optimisation of a range of thresholds and was deemed a suitable value to maximise the detection of meaningful changes in the environment whilst limiting the detection of false changes, such as
differences in water bodies as a consequence of surface roughness. The changes in the class were observed to be predominantly outside of the distribution and encroached into the tail of the ratio distribution to a value of 2.5, whereby values lower than 2.5 did not represent a change outside of the range of values for that class. As the ALOS PALSAR data has been proven to be consistent, this threshold could be applied to each study site.

The initial change detection was implemented between the baseline (2010) and 2007. This was done to maximise the detection of change features as it was assumed that greater changes would occur over a wider temporal range. Secondly, as the baseline was created for 2010 and change was being detected backwards in time, initially comparing the images with greatest temporal difference allowed changes forward in time to 2010 to be detected. This provided further information than could be attained from working incrementally backwards in time. Firstly, it provided a means of testing the reliability of the method, as the final baseline achieved from the change detection over the period of 2009-2010 should be the same as that of the 2010 baseline. Secondly, it enabled the comparison of the method for detecting change over both annual and longer time periods. A combination of these could reveal the applicability of the method for dense time-series analysis.

An outline of the steps taken to detect changes in mangrove extent between ALOS images is outline in the workflow in Figure 7.3.

7.1.5 Application to JERS-1 time-series change detection

The ratio between the JERS-1 and ALOS PALSAR imagery could not be evaluated due to the difference in the sensors. The change features were therefore separated from the class distribution by iteratively removing the tail of the distribution and testing its normality through skewness and kurtosis. This was not limited as it was for the ALOS PALSAR imagery as the temporal difference in the dataset, and subsequent changes in backscatter of the change features, was much greater. The tail of the distribution where the change objects occurred
was, therefore, over a large enough range in comparison to both the range over which the class distribution occurred and the size at which the distribution was sampled and tested for normality.

Figure 7.3: Workflow of the change detection method for ALOS PALSAR scenes. The segmentations from the two independent scenes are merged into a single segmentation. The ration of the two images is calculated and the distribution of the ratio values within the mangrove class is threshold at 2.5. This is run for the periods 2007–2010, 2007–2008, 2008–2009 and 2009–2010.

7.1.6 Post processing

Thus far the method has identified potential change features only and further analysis is required in order to differentiate these potential change features from actual class changes. To do this a number of logical contextual rules were used to separate false negatives from actual change features. The first rule defined a minimum mapping unit of 1 ha and was applied to both the JERS-1 and ALOS PALSAR change features. Features with an area less than 1 ha were not assigned as change. This threshold was not applied to individual objects but was applied to features, composed of merged adjacent objects. This was done by exporting the change columns from the RAT as individual binary change images. These images were then clumped so that adjoining pixels were grouped into image objects. These new objects could then be queried as to whether they had an area below 1 ha. Objects containing less than 16 pixels (25 m) were omitted. Further to this, specific rules were applied to the mangrove and water change objects that represent contextual restraints that would be expected in nature. These rules were different dependent on image used for the change detection.
7.1. METHOD

7.1.6.1 ALOS PALSAR

A HV backscatter (dB) value of -20 was applied to both the mangrove and water change features. If a mangrove feature had changed but maintained a backscatter value above -20 dB it was not assigned as change. Likewise, if a water change feature maintained a backscatter below -20 then it was not assigned as change. A final rule was applied to the water change features to ensure that the feature were occurring within a mangrove area. Changes outside of this area were omitted, as a water feature would not change to a mangrove feature, if the feature was a great distance from existing mangroves. To implement this rule, a proximity image was created from the 2010 mangrove baseline using GDAL. This image was then populated into the water change features and a threshold of 1000 m was applied. Water change features in excess of 1000 m from the existing mangrove extent were removed.

Image objects that conformed to these rules were identified as change features and were populated back into the RAT. A new mangrove baseline and water class extent were then defined by removing the new change objects from the previous baseline and adding them to the extent of the previous class. These were then exported as new updated extents. This method was implemented for 2010–2007, 2007–2008, 2008–2009 and 2009–2010.

7.1.6.2 JERS-1

The number of rules that can be applied to the potential change features between 1996–2010 was limited to the availability of a single horizontally polarized radar band and information that described the physical characteristics of the environment. For changes from water to mangrove a backscatter threshold greater than -10 was set and a distance from mangrove within 1000 m was applied. The distance from mangrove was achieved in the same manner as that of for the ALOS PALSAR post-processing.
7.2 Accuracy assessment

The accuracy of the change detection is provided, but is done so in two ways. The radar imagery was revealed to be prone to errors in image registration, so that a shift between the same image extent between years was noticeable. In these instances, it would be unfair to assess the performance of the method when an error may be present in the input data. In order to address this, a “user’s” accuracy assessment is provided, stating the accuracy of the change maps that are generated based on the identification of true change, whilst a second “producer’s” accuracy assessment is provided, whereby the change detection method is not punished for correctly identifying changes in image objects that were due to image registration error. The accuracy assessment was carried out by manually validating each of the change features detected over the periods, 2007–2010, 2007–2008, 2008–2009 and 2009–2010 for both mangrove loss and mangrove gain. In order to capture potential change features that were not detected by the method, a series of ‘no-change’ points were also validated. These no-change points were selected at random within a buffer surrounding the location where change was most likely to occur. This was in the water class within 1000 m of land, in the other class within 1000 m of the mangrove class and in the other class within 1000 m of water. This created a coastal buffer zone around the mangrove that extended into the water and other classes. Each of these points was buffed by 40 m to take into account the difference between the change detection and validation imagery. This process was repeated for the JERS-1 change features but due to the larger quantity of change features detected, a sample of 300 was validated at each study site.

7.3 Results

7.3.0.1 ALOS PALSAR 2007-2010 change

The results for the change detection between the ALOS imagery, for the years 2007, 2008, 2008 and 2010 are presented. Change maps were generated using an
automated approach for each of the study sites with the changes between mangrove and water detected over 4 periods. These included the change detected over the period 2007–2010, 2007–2008, 2008–2009 and 2009–2010. This was achieved by utilising a novel technique that combined an image-to-image technique using a map-to-image approach. The successful results attained by the method demonstrate the abilities of the novel map-to-image approach and demonstrated its potential despite its infancy in the field of automated change detection. The performance of the method was demonstrated through the high accuracies achieved for both the performance of the method (producer’s) and for the change maps that were produced (user’s).

Examples of the performance of the change detection are given and the full maps for each site are provided in Appendix A.2. The change results are presented in Table 7.1 and the user’s and producer’s accuracies for the detected change are presented in Table 7.2 and Table 7.3 respectively. Over the period 2007–2010 mangrove forests at the 16 study sites experienced a combined net loss, in keeping with observed trends in mangrove extent (Polidoro et al., 2010). The combined gains and losses in extent were small in comparison to the total mangrove area (2,500,000 ha) mapped, but accounted for a substantially large proportion of mangrove area in some regions (i.e. the Mahakam Delta, Kalimantan, Borneo). The study sites represent a small proportion of the global mangrove area (13,100,000 ha) and it can not be concluded as to whether global mangrove forests over these periods experienced a net gain or loss in extent.

### 7.3.0.2 Successful change detection

The mangroves of French Guiana experienced the greatest change over the period 2007–2010, with large areas of gain (Figure 7.4) and loss (Figure 7.5) of mangrove of 3,250 ha and 3,120 ha, respectively. These changes occurred along the seaward margin of the mangrove that fringe the coastline. The change was mapped with a user’s accuracy of 85.4% and 96.2% for the gain and loss of mangrove and a producer’s accuracy of 97.9% and 99.5% for the mangrove gain and mangrove loss, respectively (Table 7.2 and Table 7.3). This demonstrates the ability of the
method to monitor mangrove extent at high resolution over large geographical areas, including the entire coastlines of countries, such as French Guiana. The low kappa statistics were a consequence of the little quantity of change features detected which were often misclassified as a consequence of image registration error or noise in the radar data. The lower accuracy of the User’s accuracy than the producer’s accuracy was due to a registration error between the ALOS PALSAR scenes. A small number of undetected change objects detected in the no-change class were, therefore, capable of significantly affecting the kappa statistic. This registration error did not substantially affect the accuracy as the majority of the change features were much larger than the registration error. The registration error most adversely affected the small change features detected where the registration error was large in comparison to its size. The detection of change features over the periods 2007–2008, 2008–2009, 2009–2010 was small with a maximum of 70 ha of gain detected between 2008–2009 and a maximum loss of mangrove of 20 ha. This demonstrates that despite the large changes in mangrove over the period 2007–2010 that method was unable to detect changes on an annual basis.

7.3.1 Annual change maps

The results of the annual change maps are presented in Table 7.4. The change detection was run over the period 2007–2010 and subsequently over the periods 2007–2008, 2008–2009 and 2009–2010. Over each period the mangrove area was compared to that of the 2010 baseline. A perfect system would yield a mangrove area over the period 2009–2010 that was identical to that of the area of the 2010 baseline. This was not achieved at any of the study sites. Combined with the small quantities of change detected from Table 7.1 the monitoring system is deduced to be unable to detect changes in mangrove extent on an annual basis. It is conceivable, however, that the mangrove area in 2009–2010 would not equal that of the baseline classification as the baseline contained classification error, which would have been removed via the change detection method.

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Figure 7.4: Mangrove gain along the seaward margin of the French Guiana coastline over the period 2007–2010. The detection of gain over the annual periods 2007–2008, 2008–2009 and 2009–2010 was small.
Figure 7.5: Mangrove loss along the seaward margin of the French Guinea coastline over the period 2007–2010. The detection of loss over the annual periods 2007–2008, 2008–2009 and 2009–2010 was small.

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7.3. Results

7.3.1.1 Image registration

The basis for achieving accurate change detection results is accurately registered data. This study demonstrated that the image registration between ALOS PALSAR mosaic scenes was poor. This registration error was observed to be low (1–5 pixels) but was enough to cause substantial misclassification of mangrove change features. This was exemplified in Nigeria, whereby a large number of change features were detected along the many mangrove fringed channels in the Niger Delta but were detected due to the registration error between images (Figure 7.6). This inaccuracy was reflected in the user’s accuracy for the gain and loss of mangrove over the period 2007–2010 of 55.8% and 52.9% for areas of 980 ha and 700 ha, respectively. Despite this, the ability of the method to detect abnormalities in the class associated with change features, regardless of their cause, was promising. This was reflected in the producer’s accuracies for the same change features of 90% and 98.8% for the mangrove gain and loss features, respectively. These results revealed two important features to be considered if an operational monitoring system was to be implemented. Firstly, the registration error is unable to deliver accurate maps to the user without additional pre-processing steps to ensure that the data is registered with greater accuracy and precision. Secondly, with high quality input data the change method is capable of achieving accurate results across large geographical areas, attaining results at a high spatial resolution relative to the potential global coverage of the system.
CHAPTER 7. DETECTING CHANGE IN MANGROVE EXTENT

Figure 7.6: Registration error between 2007 and 2010 ALOS PALSAR scenes of 1–2 pixels evident in the different position of the mangrove baseline in the two scenes, despite no change in mangrove extent.
7.3. RESULTS

7.3.1.2 Classification error

Fundamental to achieving accurate change results is an accurate baseline from which changes between classes can be achieved. The baseline classifications achieved were highly accurate, yet in regions with little or no change, even small errors in the classification that were translated to errors in change detection were amplified. In some instances, narrow water channels incorrectly classified as mangrove due to the inclusion of water pixels within large mangrove objects were classified by the change detection method. The change detection method relies upon the merging of two segmentations and so the image objects are different to that of the two individual segmentations that are merged. This enables water pixels within mangrove objects from the classification to be separated, dependent on how the objects from the two segmentations are merged. This forms a new object which contains different descriptive statistics and as a consequence may be detected as a change feature defined by the thresholds used. This was exemplified at the Gulf of Fonseca, Honduras, whereby the classification of water channels as mangrove were subsequently incorrectly detected as change features (Figure 7.7). This perceived loss of mangrove was small (490 ha) yet reduced the user’s accuracy to 88% compared with the producer’s accuracy of 97.6%.

Classification error also contributed to the poor user’s accuracy at the Niger Delta, Nigeria of 52.9%. This limitation was not a function of the change detection method but highlighted the critical importance of achieving a highly accurate classification. This highlighted a weakness within the method that any errors incurred within the classification stage were directly transferred into the change detection stage. A potential solution to this could be to refine the classification during a post-classification stage, which could use thresholds on backscatter or NDVI to remove non-vegetated objects from the mangrove class or non-water pixels from the water class. Alternatively, a form of the change detection method could be run on the classified image using the data used in the classification to determine erroneously classified objects.
7.3.1.3 Minimum mapping unit

A minimum mapping unit (mmu) of 1 ha is a small quantity of change to detect when working at large scales. Although the radar imagery is Lee filtered, speckle and noise that is common within radar imagery can cause pixel values to change without a real world change occurring. This was particularly pertinent at the water/mangrove interface whereby the large contrast in backscatter values can cause subtle changes in pixel values to be falsely detected as a change feature. This was exacerbated when there was even a small registration error between images of one pixel or more. A potential solution to this would be to increase the size of the mmu so that these changes are eradicated and only meaningful change objects remain. This was observed in French Guiana (Figure 7.8) whereby large areas of change were adequately and accurately classified yet the accuracy of the change detection was inhibited by the presence of small change features that did not represent real changes. This was reflected in the user’s and producer’s accuracies of 84.5% and 97.9%, respectively. The size of the areas of mangrove gain in French Guiana vary from the mmu of 1 ha to 567.7 ha. The total area of mangrove gain in the region above 5 ha is 3,025 ha and the total area of mangrove gain below 5 ha is 296.2 ha, equitable to approximately 9% of the total gain. The increasing of the mmu to 5 ha would remove the anomalous change features, with only a small loss of potentially valid change features and increase the accuracy of the product.
Figure 7.7: Classification error at the Gulf of Fonesca, Honduras, as fine water channels are misclassified as mangrove. These features are subsequently erroneously classified as change objects.
Figure 7.8: Erroneous classification of change features due to the mmu enabling noise to be classified as change. A small shift in the imagery between the 2010 (A) and 2007 (B) ALOS PALSAR images enables the detection of small areas of change that are due to image registration error. Increasing the mmu would only allow meaningful changes to be detected and would increase the accuracy of the product.
7.3.1.4 Regrowth and landward margin

The benefit of using radar for change detection is that guaranteed consistent cloud-free imagery is available across the tropics. Furthermore, the contrast between mangrove and water is substantial so that the change between these classes is clear. The majority of mangrove change is expected to occur on the seaward margin due to common natural processes of erosion and deposition, other than on the landward margin where processes of natural large scale change are less frequent. Furthermore, changes caused by anthropogenic activity are commonly due to the conversion of mangrove to aquaculture, which have a substantial contrast with mangrove. A limitation of this assumption, however, is that mangrove changes that occur on the landward margin and between the ‘other’ class and ‘mangrove’ are not monitored. Changes with a large contrast between land cover types can be detected with radar but the change from mangrove to tropical forest is less discernible due to the similarity in backscatter of the land cover types. Abrupt changes in the landward margin would be detectable if the change in land cover was substantially different, but gradual changes with classes with little differentiation between them are not detectable with radar alone.

An attempt was made to monitor changes in the forest that were not between the mangrove and the water class at the Matang Forest Reserve, Perak, Malaysia. The mangrove at the reserve is logged on a 25 year rotation cycle for timber leaving large gaps in the mangrove forest canopy. The radar backscatter is enhanced in these areas as a consequence of increased double bounce scattering from the mangrove stumps (Thomas et al., 2015) (Figure 7.9). These changes were sought but could not be achieved with high accuracy. This was a consequence of the similarity in backscatter between the mangrove and logged areas, which although elevated above the average mangrove backscatter value, was not sufficient to detect with high accuracy. The accuracy of the detection of logging between 2007 and 2010 was 70.6%, with no separate user’s and producer’s accuracies required. The detection of changes on the landward margin would require that the radar data is supplemented with additional data, such as optical or C-band radar.
Figure 7.9: The detection of logging activities at the Matang Forest Reserve, Perak, Malaysia.
7.3.2 JERS-1 1996–2010 change

A map-to-image approach was applied to detect changes in mangrove extent between 1996 JERS-1 imagery and the 2010 baseline. This approach differed to that of the change detection using ALOS PALSAR imagery by omitting the image-to-image step of image ratioing. This could not be achieved as the images were acquired by two separate sensors and the use of image ratioing would not be appropriate. The change detection was carried out using the JERS-1 object values. Mangrove forests over the period 1996–2010 experienced a net gain in extent, which is against the observed trend in mangrove forest extent (Polidoro et al., 2010) over the past century. A portion of this was the result of classification error that caused a bias towards an increase in mangrove forest extent. Despite this increase, a gain in mangrove area does not impart any information on the health of the forest. Changes along a coastline are common, often affecting young mangroves, yet anthropogenic removal and degradation within the forest affects the mature mangrove and causes an unnatural disturbance in the ecosystem. The method was capable of achieving satisfactory results with overall user’s accuracies for the mangrove gain of 62.7% and mangrove loss of 68.3% and high producer’s accuracies for mangrove gain and loss of 94% and 93.6%, respectively. The results are presented in Table 7.1 with the User’s and Producer’s accuracies for the change detection in Table 7.2 and 7.3. The success of the method enabled change detection to be carried out over a large temporal resolution with a difference in the JERS-1 imagery and the mangrove baseline classification of 14 years. This was able to provide an advantage over other change detection methods that may be limited to using imagery from one specific sensor or sensor type. This would enable trends in the change in mangrove extent to be observed over a wide temporal range. Examples of the change detection are provided with the results for each study site provided in Appendix A.2.1.

7.3.2.1 Large scale changes

The mangroves of the Mahakam Delta, Kalimantan, have been historically heavily disturbed because of the installation of aquaculture, causing the removal of large
areas of mangrove (Rahman et al., 2013). The proposed method was able to successfully detect this loss of mangrove due to the contrast in backscatter between the mangrove forest and the surface of the aquaculture pond. This demonstrates the ability of the method to highlight changes in mangrove extent as a direct consequence of anthropogenic activity and the ability of the method to provide users with knowledge on human induced forest loss. The ability to deliver this information to policy makers was a key aim and this result demonstrated that this has been achieved. The mangrove loss over the period was 23,000 ha (Figure 7.10) with a small quantity of gain of 1,490 ha. This loss and gain was mapped with a user’s accuracy of 68% and 83% and a producer’s accuracy of 98.3% and 97.2%, testament to the performance of the method. Furthermore, the method demonstrated that change detection can be carried out using imagery independent of that used for the classification. This provides the method with longevity into the future with an ability to utilise current and future satellite imagery.

7.3.2.2 Limitations

The limitations encountered in the detection of changes using JERS-1 imagery were not different from those encountered using ALOS PALSAR imagery, on account of them both being radar images. Neither dataset has any additional limitations than the other. Classification error within the 2010 baseline caused subsequent errors within the change detection using JERS-1 imagery, much in the way that it did for the change detection between ALOS PALSAR scenes. Whilst this demonstrated that the method was able to detect anomalies in the class distribution, it lowered the accuracy of the product and the subsequent user’s accuracy. This was reflected in the producer’s accuracies which were substantially higher than the user’s accuracies at each study site.

The size of the minimum mapping unit (mmu) and the inability to detect changes on the landward margin of the mangrove were limitations, as they were for the detection of change between ALOS PALSAR images. The noise introduced into the detection of change using JERS-1 imagery was greater than that of the detection of change between ALOS PALSAR scenes, with a greater number of small features
Figure 7.10: The detection of widespread mangrove loss at the Mahakam Delta, Kalimantan.
detected. The inability to detect inland changes on the landward margin of the mangrove was not sensor specific but a limitation of using radar imagery.

The greatest limitation to impinge upon the use of JERS-1 imagery for change detection was the larger registration error between the ALOS PALSAR and the JERS-1 imagery than between the ALOS PALSAR scenes alone. This was reflected in the substantially lower user’s accuracies with the combined mangrove gain and loss of 62.7% and 68.3%, respectively. These accuracies were substantially lower than the change detection between ALOS PALSAR scenes with the lowest gain and loss accuracies of 81.5% and 78.3%. This limits the imagery from being directly used as part of a monitoring system without the registration error being corrected in a pre-processing step.

7.4 Discussion

A change detection method was successfully implemented using a novel map-to-image approach and was demonstrated to be capable of mapping change features from both the same and different sensors from which the classification was derived. Two subtly different approaches were used, dependent upon whether ALOS PALSAR or JERS-1 was used for the change detection. It was not a requirement for the data to be acquired from the same sensor or even to be of the same mode, although using data from the same sensor enabled more in-depth change detection to be achieved. This was exemplified through the use of ALOS PALSAR imagery whereby image ratioing was used to detect change features as opposed to the use of pixel values alone where the imagery for classification (ALOS PALSAR) and change detection (JERS-1) were different.

The approach was able to successfully detect both large and small scale changes down to the minimum mapping unit (mmu) of 1 ha. The use of radar was successful in detecting changes in mangrove extent, enabled by the ability of radar imagery to be acquired irrespective of cloud cover and atmospheric conditions, guaranteeing the availability of data over a dense temporal range. This could not be supplied by optical imagery that is consistently inhibited in tropical regions.
The results revealed the dynamic nature of natural changes to mangrove extent which can cause large increases or decreases in mangrove extent. The results were also able to detect the effect of anthropogenic impact on the mangrove environment, particularly the removal of mangrove forest for aquaculture. The method was not capable of detecting changes outside of the change to or from mangrove and water and performed poorly at detecting small increments of change on an annual basis, providing better results at detecting larger changes, either due to sudden events or cumulative change over a larger temporal scale.

The method utilised a novel method of map-to-image change detection that offered a number of advantages over the current existing methods that include map-to-map and image-to-image methods. A map-to-image technique was used over a map-to-map technique as it does not require that two independent results are compared. A fundamental limitation of map-to-map change detection is that its accuracy is dependent upon the accuracy of the input maps, requiring that multiple accurate maps are required for repeated change detection analysis (Alesheikh et al., 2007; Walter, 2004). This current method does not require that the errors present in more than one map need be considered. A benefit of a map-to-map technique is that a full matrix is available of the changes between all classes (Singh, 1989; Coppin et al., 2004) although this current study is concerned only with the changes between two classes and this level of detail was not required.

The map-to-image change detection utilised an image-to-image technique to enhance the detection of change features between images acquired by the same sensor. Image-to-image techniques use image differencing, image ratioing, change vector analysis or image transformation to compare pixel values between two images in search of change features (Coppin et al., 2004; Singh, 1989). This current study was interested only in the change between two classes and not the change that occurred throughout all classes which image-to-image techniques detect. This method, however, was able to incorporate the image-to-image technique of image ratioing between images acquired by the same sensor.
Image ratioing was conducted between ALOS PALSAR scenes before the map-to-image technique was applied. Image differencing is the most common technique (Coppin et al., 2004; Lyon et al., 1998) for image-to-image change detection but is unsuitable for use with radar imagery due to speckle. Other methods such as Change Vector Analysis and Image transformation are capable of acquiring accurate results (Im et al., 2008; Chen et al., 2003) but are substantially more challenging to use consistently with little user input over a large number of scenes, which would be required at the global level. The use of image ratioing, however, was not limited by radar speckle although it remains compatible only with imagery from the same sensor.

Image ratioing has traditionally been limited by the difficulty in the selection of a threshold to detect change features from the ratio image as the distribution of values is typically bi-modal (Alqurashi and Kumar, 2013; Coppin et al., 2004). This proposed method overcomes this limitation through the map-to-image technique that detects change within one class at a time, so that the histogram of values is univariate so a threshold can be applied either manually or automatically. Ratio values that are indicative of changes to and from mangrove and water classes are determined separately. This is a product of the change to and from the mangrove class already being known and not requiring the search for change outside of these classes. This is a potential limitation if mangrove changes occur between another land cover type (i.e. tropical rainforest).

The map-to-image technique applied in this work was able to detect changes between radar images acquired from different sensors in an automated manner. This has not readily been achieved before due to the requirement for the accurate calibration between imagery. This map-to-image technique enabled change detection between sensors and modes to be achieved without the need to calibrate the imagery due to the method relying upon class statistics withdrawn from one image. Existing change detection between images acquired from different sensors have relied upon map-to-map techniques for measuring changes in Alaskan wetlands (Clewley et al., 2015) and measuring biomass changes in tropical forest
(Mitchard et al., 2011), requiring the post-classification analysis of independent maps. This current study was unable to achieve two separate classifications for change detection due to data availability and was designed with the intention that change detection could be applied regularly and repeatedly at high temporal resolution, without the requirement for independent classifications. The approach of using class statistics was able to detect changes in a chosen class using an automated threshold that was unique to each input image. This was applied to, but not limited to, radar imagery and could be used in conjunction with other modes of data for detection of change features. This approach is novel and enabled the automated change detection of classified imagery acquired at different times from different sensors. A limitation of this method is that it is only applicable to one class at a time although it can be scripted to be applied to many classes or run simultaneously for each class.

Limitations that the method could not overcome are inherent within all change detection approaches. A source of error beyond the control of the change detection is the reliance upon accurate input data, whether this be an accurate map or well registered images. Classification error within a map could potentially be erroneously detected as change features so that change features detected, therefore, are a combination of real change features and improvements to the classified map. Similarly, poorly registered imagery used within a map-to-image technique would lead to the detection of erroneous change features as land cover types are confused due to the location error between the map and the image. The separation of correctly and erroneously identified change features cannot be achieved by the change detection approach but could be addressed during a post-classification step. The correction of misclassification error would improve the change detection results by reducing the number of false positive change features detected whilst ensuring accurate co-registration between imagery during a pre-processing stage would further improve the change detection results.


7.5 Conclusion

This study was able to generate an automated method of detecting changes using a novel map-to-image technique that was capable of using imagery from any sensor or of any image modality. This was done by relying upon the class statistics calculated from the input image and not the image values directly. This offered an advantage over exiting map-to-map techniques that require intensive processing to retrieve multiple classifications for comparison and image-to-image techniques that are limited to using imagery from the same sensor. This method was capable of detecting changes over temporal scales of 1, 4 and 14 year periods. The detection of change features performed better over large time periods than on an annual basis. The change features were detected with a producer’s accuracy of in excess of 90% with a lower user’s accuracy the consequence of registration error between the classification map and the input imagery. The detection of mangrove change other than to and from water remains a substantial challenge due to the similarity in backscatter between mangroves and other forest land cover types.

7.5.0.1 Future recommendations

This method could be applied to mangrove forests globally but would need to be refined in the following aspects in order to achieve the most accurate and meaningful results:

**Image Registration** The cause of the lower user’s accuracies over the producer’s accuracies was a consequence of the registration error between the imagery from which the classification was derived and the imagery input into the change detection. Adequate pre-processing to co-register the imagery would substantially increase the user’s accuracy of the results.

**Monitoring Period** The detection of change features on an annual basis performed poorly in comparison to the detection of change features over larger time periods. This was a function of small incremental changes not having sufficient contrast on an annual basis within the image object to be detected
as a change feature within the class statistics. Large, sudden changes or those that occurred over a large time period were more accurately detected. To incorporate this method into a global monitoring system the regularity at which the detection of change features is applied should be considered.
Chapter 8

Conclusions and contribution to a global monitoring system

This chapter concludes the thesis by presenting the major outcomes of the study and their contribution to a mangrove monitoring system before suggesting avenues of future research that could be undertaken.

8.1 Major findings and conclusions

The aim of this study, provided in Chapter 1 was to:

- Develop a method that will yield information for policy and decision makers. This method should highlight the causes and distribution of changes in mangrove extent, update the existing mangrove baseline and map changes on both an annual and decadal timescale.

This aim could be achieved through successfully answering the following research questions, through the achievement of a number of accompanying objectives:

1. What is the current distribution of changes and their cause in mangrove extent across their range?

2. What is the current extent of mangrove forests?
3. How have mangrove forests responded to drivers of change? Can these changes be monitored in an automated manner?

Each of these research questions were addressed and the results of each were evaluated. The following provides a summary of the main conclusions derived from the completion of these objectives before actions to improve the findings are suggested.

8.1.1 What is the current distribution and the causes of change in mangrove forest extent across their range?

- Mangrove forest extent was observed to have undergone substantial change across its entire range through a combination of natural and anthropogenic forces.

- Within 1172 $1^\circ \times 1^\circ$ tiles examined, 12% demonstrated mangrove loss as a consequence of anthropogenic activity with additional evidence of change prior to the JERS-1 SAR data observed in over 38% of tiles. The most common cause of anthropogenic loss (10%) was conversion to aquaculture/agriculture and was most prominent in Southeast Asia.

- The combined anthropogenic causes of mangrove loss occurred in $1^\circ \times 1^\circ$ tiles where >40% of the world’s mangrove area was located.

These results demonstrated that mangrove forests are threatened across their entire range by anthropogenic activity and that the monitoring of these important ecosystems is warranted and required if their long term existence is to be preserved.

8.1.2 What is the current extent of mangrove forests? Can this be derived in detail at large geographical scales for a single point in time?

- In excess of 2.5 million ha of mangrove forest was classified using a combination of Landsat and ALOS PALSAR imagery.
A refinement of the existing mangrove maps provided an efficient method of collecting a large quantity of training data.

A machine learning algorithm (Random Forests) was able to classify mangrove extent with an accuracy in excess of 90% and improve upon the results of the existing maps.

The mapping of mangrove forests over large areas was achievable using a GEOBIA approach without any dependence upon proprietary software.

Sources of error were provided by registration error between datasets, the performance of the segmentation algorithm and quality of the input data.

The successful achievement of this objective enabled a method to be developed to map mangrove extent across the tropics, updating the existing mangrove baseline by over a decade. The method was capable of achieving the first stage of an active monitoring system by attaining an accurate mangrove baseline classification, from which changes in extent could be mapped.

8.1.3 How have mangrove forests responded to drivers of change? Can these changes be monitored in an automated manner?

Natural and anthropogenically induced changes in mangrove extent were mapped at study sites across their range over a variety of timescales.

A novel map-to-image approach was implemented for the automated detection of change between 1996–2010.


Mangrove changes could not be successfully detected on an annual basis.

Spaceborne radar was identified as being capable of providing consistent data for the monitoring of mangrove extent.

A novel approach to change detection was developed that was capable of detecting
8.2 Role within an operational monitoring system

The method of mapping and monitoring changes in mangrove extent had been demonstrated and the results achieved have been accurate. The aim of this study was to develop a method that would contribute to a global mangrove monitoring system. The expansion of this work into an operational system would have a number of advantages over current initiatives and would be capable of delivering the information sought by policy and decision makers, to ensure the future preservation of mangrove ecosystems.

An operational monitoring system would have a number of advantages over existing monitoring systems. This approach is able to provide information on changes in mangrove extent on up to an annual basis, providing data at a greater temporal resolution than systems such as GlobCover, GLC2000, Mangrove forests of the world and Mangrove forest distribution of the world. Although some of these can provide updates on an annual basis, the MODIS Land Cover product is supplied at a resolution of 250 m and not at the high spatial resolution of this work. Global Forest Cover maps are able to provide annual products at a spatial resolution of 30 m but do not include a mangrove specific class and are not aimed at specifically mapping and monitoring mangrove extent, leaving the interpretation of mangrove forest extent to the user. The latest monitoring system proposed by Hamilton and Casey (2014) provides mangrove specific information on an annual basis, yet is confined to monitoring change within a known extent of mangrove only. The monitoring system also does not provide detailed maps based on presence and absence but on continuous tree cover. Other global for-
est mapping and monitoring efforts have either not included a mangrove specific class, have generated a product for a single point in time or were produced with a coarse spatial resolution. The monitoring system proposed here initiates a new classification in order to include mangrove outside of previously known extents and is able to include new mangrove growth outside of this, provided as annual maps based on high resolution mangrove presence and absence information.

A mangrove monitoring system borne out of the methods developed in this study would be able to retrieve information on mangrove extent and subsequent information on carbon storage, biodiversity and local livelihood support. The ability of a monitoring system to attain important information on each of these ecosystem services is crucial for their preservation. The importance of these ecosystem services and the information that a monitoring system could yield is outlined.

8.2.1 Mangrove monitoring: mangroves

This mangrove monitoring system would be able to monitor the change in extent that has previously occurred, highlighting regions that have suffered the greatest losses. During the 1990s alone, mangrove loss was estimated at 1% per year, a rate twice that of tropical rainforest loss over the same period (Mayaux et al., 2005) culminating in 11 of the 70 true mangrove species meeting the criteria of the three RED categories of threatened species (Polidoro et al., 2010). The largest contributor to this decline in mangrove forest has been the rapid expansion of aquaculture, particularly in developing nations (Valiela et al., 2001; Primavera, 2000) and have been exacerbated by the development of the coastal zone (Upadhyay et al., 2002; Benfield et al., 2005) and population growth (FAO, 2012, 2013).

The expected impacts of climate change upon mangroves is uncertain and could have both beneficial and detrimental impacts upon mangrove extent. An operational system built upon the methods developed in this study would be able to map and quantify historic changes in extent and provide an annually updated baseline. This would reveal regions where mangrove forests are under increasing anthropogenic pressure and would aid in the understanding of the response of these ecosystems towards climate change.
8.2. ROLE WITHIN AN OPERATIONAL MONITORING SYSTEM

8.2.2 Mangrove monitoring: ecosystem services

The importance of mangrove monitoring extends beyond that of their diminishing extent but the potential loss of the invaluable ecosystem services that they provide. Mangrove forests are capable of attaining biomass up to the high values of 460 t ha$^{-1}$ (Putz and Chan, 1986). This equates to large quantities of carbon being stored within large forest extents. In addition to this, the mud soils that mangroves accumulate are capable of storing much larger quantities of carbon. Soils ranging from 0.5–3 m in depth are capable of storing an average of 1023 Mg C ha$^{-1}$ (Donato et al., 2011). The combined loss of these forests and their soils is estimated to release 0.02–0.12 Pg C yr; a value equitable to 10% of total carbon emissions from global deforestation, despite accounting for <1% of global forest area (Donato et al., 2011).

The role that a mangrove monitoring system can play in carbon accounting is exemplified in Table 8.1. A mean biomass value from the mangrove biomass map of Hutchison et al. (2014) was extracted using the classified mangrove baseline and change regions for the periods 1996–2010 and 2007–2010. The map of Hutchison et al. (2014) is of AGB only and carbon values were calculated as being half of the biomass (Fang et al., 2001). The values extracted demonstrate the large quantities of carbon that are stored above ground within mangrove forests and the potentially large losses and gains that accompany changes in mangrove extent. The carbon gain values are potential values only as not all mangrove gain detected would be at its maximum biomass value, which varies with age. Similarly, mangrove loss along the seaward margin of the forest may not be representative of mature mangrove vegetation. These values, therefore, indicate the maximum in the carbon flux and further work considering Earth observation data at individual time intervals would be required to reduce this uncertainty. This information is of direct importance to inform policy making on mangroves forests as a source of and sink for carbon emissions. This information would be directly applicable to the REDD+ carbon accounting scheme and would be able to address Aichi Target 15 through providing information on the potential enhancement of carbon stocks.
Mangrove forests play a vital role in ecosystem support and can be the linchpin in supporting an entire ecosystem. Mangrove forests inhabit the coastal zone at the boundary between the aquatic and terrestrial biomes and are, therefore, able to support a broad range of fauna. These fauna use the mangrove for a multitude of reasons, including as a direct food source for herbivorous species and an indirect source for carnivorous species. Mangroves offer shelter to some species and are important breeding grounds and nurseries for others. An operational system built on the methods developed in this study would be capable of monitoring diminishing mangrove extent and use this as a proxy for monitoring wider ecosystem health and loss of biodiversity.

Mangroves also provide a range of ecosystem services to local populations, particularly to those that inhabit the coastal zone of developing nations. Local populations rely on mangroves for a wide variety of resources including timber, building materials and hunting and fishing grounds (Bandaranayake, 1998; Nfotabong-Atheull et al., 2011). Mangroves also provide indirect services such as attenuating storm surges and tsunamis, offering shoreline protection to populations and property (Danielsen et al., 2005). An operational monitoring system would be able to reveal regions that are at increased risk of poverty due to a loss of resources and that are at increased vulnerability to large oceanic events.
### Table 8.1: Carbon content of mangrove forests and gains and losses with changes in forest extent.

<table>
<thead>
<tr>
<th>Study Site</th>
<th>2010 Baseline</th>
<th>Error C Gg ha$^{-1}$</th>
<th>1996-2010 Gain</th>
<th>Error C Gg ha$^{-1}$</th>
<th>1996-2010 Loss</th>
<th>Error C Gg ha$^{-1}$</th>
<th>Net change C Gg ha$^{-1}$</th>
<th>% of total biomass 2007-2010</th>
<th>Gain C Gg ha$^{-1}$</th>
<th>Error C Gg ha$^{-1}$</th>
<th>2007-2010 Loss</th>
<th>Error C Gg ha$^{-1}$</th>
<th>Net change % of total biomass 2007-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amapa</td>
<td>12,119.35</td>
<td>± 557.89</td>
<td>403.76</td>
<td>± 23.42</td>
<td>700.10</td>
<td>± 49.01</td>
<td>-296.34</td>
<td>2.45</td>
<td>16.67</td>
<td>± 1.02</td>
<td>120.39</td>
<td>± 4.45</td>
<td>-103.72</td>
</tr>
<tr>
<td>Bragança</td>
<td>21,353.85</td>
<td>± 1,473.42</td>
<td>456.09</td>
<td>± 20.98</td>
<td>332.94</td>
<td>± 91.22</td>
<td>123.15</td>
<td>0.58</td>
<td>28.03</td>
<td>± 2.52</td>
<td>42.47</td>
<td>± 1.44</td>
<td>-14.44</td>
</tr>
<tr>
<td>São Luís</td>
<td>14,899.40</td>
<td>± 1,834.45</td>
<td>273.32</td>
<td>± 13.67</td>
<td>483.76</td>
<td>± 19.35</td>
<td>-210.44</td>
<td>1.45</td>
<td>13.41</td>
<td>± 0.05</td>
<td>107.32</td>
<td>± 3.97</td>
<td>-93.90</td>
</tr>
<tr>
<td>Todos os Santos</td>
<td>5,122.92</td>
<td>± 1,473.42</td>
<td>424.52</td>
<td>± 42.45</td>
<td>399.58</td>
<td>± 17.34</td>
<td>114.93</td>
<td>2.24</td>
<td>2.78</td>
<td>± 0.09</td>
<td>1.85</td>
<td>± 0.14</td>
<td>0.93</td>
</tr>
<tr>
<td>Guaraú</td>
<td>8,635.29</td>
<td>± 1,460.00</td>
<td>674.74</td>
<td>± 30.77</td>
<td>339.93</td>
<td>± 50.31</td>
<td>114.42</td>
<td>3.65</td>
<td>38.63</td>
<td>± 1.74</td>
<td>56.01</td>
<td>± 1.99</td>
<td>-17.18</td>
</tr>
<tr>
<td>French Guiana</td>
<td>14,415.33</td>
<td>± 1,834.45</td>
<td>1,389.18</td>
<td>± 125.90</td>
<td>860.38</td>
<td>± 29.56</td>
<td>710.12</td>
<td>4.93</td>
<td>329.70</td>
<td>± 6.92</td>
<td>316.51</td>
<td>± 1.58</td>
<td>15.19</td>
</tr>
<tr>
<td>Guinés Bissau</td>
<td>50,236.93</td>
<td>± 3,164.93</td>
<td>4060.53</td>
<td>± 101.51</td>
<td>4070.93</td>
<td>± 110.75</td>
<td>1,652.85</td>
<td>3.29</td>
<td>177.06</td>
<td>± 15.00</td>
<td>127.92</td>
<td>± 8.04</td>
<td>40.14</td>
</tr>
<tr>
<td>Honduras</td>
<td>6,192.20</td>
<td>± 629.20</td>
<td>709.22</td>
<td>± 31.91</td>
<td>217.07</td>
<td>± 12.16</td>
<td>432.05</td>
<td>5.71</td>
<td>44.74</td>
<td>± 3.18</td>
<td>40.60</td>
<td>± 0.97</td>
<td>4.14</td>
</tr>
<tr>
<td>Mozambique</td>
<td>1,667.73</td>
<td>± 248.79</td>
<td>50.99</td>
<td>± 3.11</td>
<td>56.51</td>
<td>± 2.66</td>
<td>-5.51</td>
<td>0.33</td>
<td>1.38</td>
<td>± 0.02</td>
<td>16.54</td>
<td>± 1.03</td>
<td>-15.16</td>
</tr>
<tr>
<td>Sumatra</td>
<td>17,593.73</td>
<td>± 1,671.40</td>
<td>591.25</td>
<td>± 50.85</td>
<td>111.01</td>
<td>± 4.88</td>
<td>-480.24</td>
<td>2.73</td>
<td>45.57</td>
<td>± 3.65</td>
<td>28.04</td>
<td>± 1.37</td>
<td>17.53</td>
</tr>
<tr>
<td>Mahakam Delta</td>
<td>18,180.79</td>
<td>± 548.59</td>
<td>174.34</td>
<td>± 2.96</td>
<td>2,691.10</td>
<td>± 75.35</td>
<td>-2,516.77</td>
<td>30.74</td>
<td>115.83</td>
<td>± 4.75</td>
<td>107.64</td>
<td>± 2.37</td>
<td>8.19</td>
</tr>
<tr>
<td>South Kalimantan</td>
<td>7,343.49</td>
<td>± 697.63</td>
<td>352.37</td>
<td>± 16.21</td>
<td>833.56</td>
<td>± 21.22</td>
<td>-141.20</td>
<td>1.92</td>
<td>62.48</td>
<td>± 3.50</td>
<td>39.98</td>
<td>± 0.72</td>
<td>22.49</td>
</tr>
<tr>
<td>Penang</td>
<td>4,416.44</td>
<td>± 180.83</td>
<td>105.13</td>
<td>± 19.34</td>
<td>24.03</td>
<td>± 1.27</td>
<td>-81.10</td>
<td>1.84</td>
<td>5.01</td>
<td>± 0.00</td>
<td>7.01</td>
<td>± 0.50</td>
<td>-2.00</td>
</tr>
<tr>
<td>Nger Delta</td>
<td>42,524.83</td>
<td>± 1,786.04</td>
<td>1,102.97</td>
<td>± 2.21</td>
<td>131.59</td>
<td>± 0.27</td>
<td>-969.38</td>
<td>2.28</td>
<td>111.90</td>
<td>± 11.19</td>
<td>79.93</td>
<td>± 0.96</td>
<td>31.97</td>
</tr>
<tr>
<td>Kalimantan</td>
<td>700.38</td>
<td>± 22.81</td>
<td>171.47</td>
<td>± 4.12</td>
<td>44.23</td>
<td>± 1.77</td>
<td>127.25</td>
<td>16.73</td>
<td>23.28</td>
<td>± 0.61</td>
<td>3.10</td>
<td>± 0.12</td>
<td>20.17</td>
</tr>
<tr>
<td>Venezuela</td>
<td>18,877.71</td>
<td>± 1,220.19</td>
<td>441.06</td>
<td>± 27.35</td>
<td>287.20</td>
<td>± 8.62</td>
<td>153.86</td>
<td>0.83</td>
<td>49.58</td>
<td>± 1.74</td>
<td>53.00</td>
<td>± 0.90</td>
<td>-3.42</td>
</tr>
</tbody>
</table>
8.2.3  Mangrove monitoring: policy relevance

An operational mangrove monitoring system, built upon this study, would be able to provide products and information that would inform policy and decision makers. This information is currently not routinely available, despite the observed response of mangroves to a range of external forces. The results of this work are able to provide the data required by policy makers, such as the changes in mangrove extent and associated gains and losses in carbon and the provision of other ecosystem services. To actively deliver information to policy and decision makers a monitoring system must be developed, implemented, consistently evaluated for quality and accuracy and fundamentally, must be capable of addressing the aims, targets and needs of policy. Annual mangrove loss maps and 5-year mangrove gain maps would be suitable products to deliver the much needed information to inform policy and could be used to satisfy the needs of a number of international targets and treaties. The relevance of the products for a number of these is provided in Table 8.2.
Table 8.2: A number of the policies and treaties that the mapping and monitoring of mangroves is able to directly support.

<table>
<thead>
<tr>
<th>Policy</th>
<th>Policy requirement</th>
<th>Support provided by GMW products</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Ramsar Convention</td>
<td>Maps of extent and condition of wetlands</td>
<td>GMW products are able to directly satisfy this requirement and directly provide the Ramsar Convention with the data required</td>
<td>Ramsar 2012, 2005; MacKay et al. 2009</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>Aid MRV of carbon stocks for REDD+ in developing nations</td>
<td>GMW products are able to satisfy the monitoring, reporting and verification of changes in mangrove extent and can be used to monitor fluxes in mangrove stocks</td>
<td>Lawrence 2012</td>
</tr>
<tr>
<td>Convention on Biological Diversity (CBD)</td>
<td>Stopping and reversing loss of biodiversity</td>
<td>GMW products are able to highlight regions that are suffering loss and degradation and associated losses in biodiversity. These regions can then be targeted for preservation</td>
<td>Pereira et al. 2013; CBD 2011</td>
</tr>
<tr>
<td>Aichi Targets:</td>
<td></td>
<td>GMW products will highlight regions suffering from the greatest losses. The targeting of these regions for preservation will sustain their habitat function</td>
<td>Gong and Ong 1990; Chong et al. 2013</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GMW products will be able to monitor that logging activities (i.e. the Matang forest Reserve, Perak, Malaysia) are done sustainably provided the time to recuperate and their ecosystem function is maintained</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Many mangrove forests are within protected areas. GMW products will be used to ensure that these forests remain undisturbed by anthropogenic activity</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>GMW products can be used to monitor the regrowth and restoration of mangrove forests, through both natural and anthropogenic causes</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>The GMW products will be able to measure flux in mangrove forest extent and consequently can be used to monitor potential changes in carbon stocks with changes in forest extent</td>
<td>Fatoyinbo and Simard 2013</td>
</tr>
</tbody>
</table>
8.3 Further work

The accuracies attained from the mangrove baseline classification and change detection demonstrate the performance of the method and its potential for being utilised within an active monitoring system. In order for this to be an operational system, a number of recommendations are provided.

8.3.1 Image registration

The greatest source of error within the change detection results was that of image registration error between datasets, that was also a cause of some classification error. It is recommended that the data is co-registered for use although this would add an additional step into the processing chain. Despite this it would substantially improve the user’s accuracy of the change detection maps.

8.3.2 Segmentation

The segmentation algorithm performed well and enabled a GEOBIA approach to be applied, but it was unable to perform satisfactorily in complex environments. The narrow dendritic nature of some mangroves represent a complex environment whereby an image object is formed that is larger then the mangrove fringe. This caused the object to contain more than one land cover type and the statistics that describe that object were not representative. The accuracy of these mangroves may be reduced but could be improved with the use of a segmentation that is able to account for shape as well as spectral differentiation. These segmentations are available within proprietary software but thus have other limitations, such as the inability to segment large datasets.

8.3.3 Land cover differentiation

A source of error that occurred during the classification of the baseline was the confusion of mangrove with other forested land cover types. To remedy this, it is suggested another dataset is used to differentiate them. This is suggested given the recent launch of ESA’s Sentinel-1 C-band radar satellite which will provide
freely available radar data for the whole of the tropics. This additional data, at C-band, could differentiate mangroves from other forested land cover types based upon their structure.

8.3.4 Monitoring period

The change detection results were observed to achieve more accurate results over larger time periods between the baseline and the input change detection imagery, due to the size of the change feature. Large and sudden losses in mangrove forest (i.e. aquaculture) could be detected on an annual timescale but incremental increases due to natural processes could not. It is, therefore, suggested that the loss of mangrove is monitored on an annual basis whilst incremental increases in mangrove are monitored on an at least 4-year period.
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Appendix A

A.1 Mangrove Classification Maps
Figure A.1: Classification of the mangroves within the Gulf of Fonseca, Honduras.
Figure A.2: Classification of mangroves along the Bragantina coastline, Brazil.
Figure A.3: Classification of mangroves at Sao Luis, Brazil.
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