Project 1.4 Remote Sensing for Environmental Monitoring and Management in the Kimberley: Phase 1 Report

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Atmospherically corrected, pan sharpened to 15 m resolution, colour corrected subset of a Landsat 8 Operational Land Imager (OLI) overpass for the 1st of May 2013 showing Montgomery Reef and surrounds. Landsat data accessed from USGS archive and processed by Mark Broomhall, Remote Sensing and Satellite Research Group, Curtin University.

Remote Sensing for Environmental Monitoring and Management in the Kimberley

Executive summary

The project is tasked with determining if there are cost effective options for utilizing remote sensing for assisting with long term monitoring, evaluation and reporting (MER) of the Kimberley. A survey of DPaW asset managers provided a good understanding of the specific condition and pressure metrics utilised in monitoring condition of and pressure affecting assets. The project will now compare the specific requirements of the management agencies with the technical and operational constraints of the various remote sensing technologies that are available.

Management Implications: Knowledge to action

1. Introduction

The Kimberley is the northernmost region of Western Australia with a land area of over 420,000 km^2. The vast area of the Kimberley is characterized by very remote and often inaccessible locations, including pristine wilderness areas, many protected by National Park status. The coastal ocean region associated with the Kimberley comprises over 2,500 islands, with many of the islands and reefs located within existing and proposed Marine Parks. The current major uses of the coastal waters include traditional Indigenous use, marine tourism, commercial and recreational fishing, pearling, aquaculture and oil and gas and iron ore port facilities. There is limited scientific knowledge of this pristine and ecologically complex area.

The Kimberley Science and Conservation Strategy (WA Government, 2011) states, "the Kimberley is at a critical point, with increasing recognition of its development potential, including development of rich offshore petroleum resources, the expansion of the Ord Irrigation Scheme, an expanding international profile and increasing visitor numbers as well as a growing population". The WA Government aim to "recognize and conserve one of the world's last great wilderness areas" (WA Government, 2011). One aspect of the strategy is to support collaborative research in the form of the Kimberley Marine Research Program (Simpson, 2011). The KMRP aims to undertake a program of marine research to support management of the proposed marine parks and coastal waters outside the marine parks (see Figure 1).

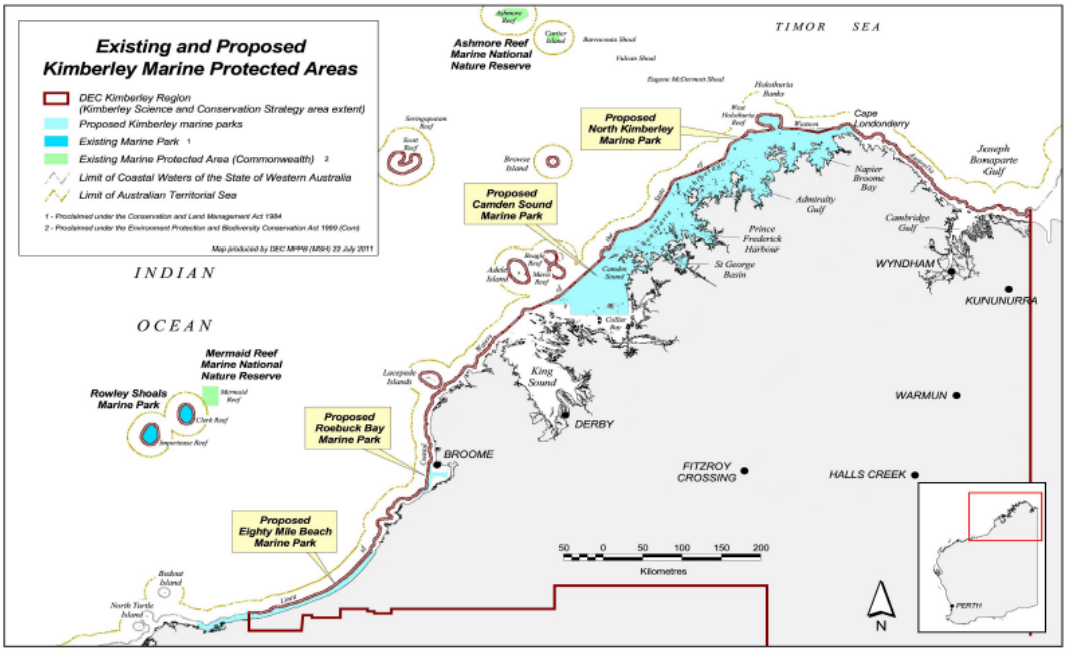

Figure 1 Map of the Kimberley showing Kimberley Science and Conservation Strategy boundary and existing and proposed marine parks. [Image from the KMRP Science Plan (Simpson 2011)].

The KMRP recognizes the fact that the Kimberley marine area is extensive and remote, and although the financial investment in the research is significant, it is not feasible to investigate the whole in its entirety. There is potential for Remote Sensing technologies to support some of the research activities, as well as some of the needs of the agency, the Department of Parks and Wildlife (DPaW), charged with managing the Kimberley resources. Australia's Satellite Utilization Policy (2013) states, "Australia aims to achieve on-going, cost effective access to the space capabilities on which the nation relies now and into the future". The policy recognizes the current utilization of satellite technologies but also aims to support development and uptake of new and emerging technologies. The policy states, "Space capabilities are the only way to effectively monitor Australia's environment" and quote a joint report from the Australian Academies of Science and Technological Sciences and Engineering that called space measurements "the single most important and richest source of environmental information for Australia".

From Ward et al. (1998) with relation to National State of the Environment reporting for Estuaries and the Sea, "In order to assess changes in the environment over time it is necessary to have indicators against which environmental performance may be reviewed. As pointed out in "Australia: State of the Environment 1996":

> "In many important areas, Australia does not have the data, the analytical tools or the scientific understanding that would allow us to say whether current patterns of change to the natural environment are sustainable. We are effectively driving a car without an up-to-date map, so we cannot be sure where we are. Improving our view of the road ahead by enhancing the environmental data base is a very high priority. Our intended destination is a sustainable pattern of development, but it is not always clear which direction we need to take to get there".

The Kimberley Marine Research Program (KMRP) is a $30M program of research investment to better understand the Kimberly's marine environment and how to build resilience through management.

The Kimberley region (Map 1) presents a pristine, remote, and expensive region to carry out on-ground works that promote conservation. Within the KMRP, research will be conducted to build knowledge of the structure, function and threatening processes affecting the Kimberley, and information and protocols to support management of the proposed marine parks and coastal waters (Map 2).

As one of the 25 science projects of the KMRP, Project 1.4 will assess the potential of remote sensing technologies to determine if/how they can play an important role in supporting some of the needs of government agencies (primarily DPaW, but also Department of Fisheries (DoF), Department of Transport (DoT) etc.) charged with ensuring the Kimberley is well managed into the future.

Remote Sensing technologies in this context are focussed primarily on satellite-borne passive sensors but also include discussion on some airborne passive sensors (e.g. hyperspectral and "standard" photography). We acknowledge the use of *in situ* remote sensing instruments such as cameras mounted on poles, and also "autonomous" (but not necessarily remote sensing) instruments that allow collection of data in remote locations, for example moored temperature loggers. In the context of this review, these autonomous and remotely located *in situ* sensors may provide valuable calibration and validation data for the remotely sensed data collected from satellite and airborne sensors. The passive space and airborne sensors discussed here all detect electromagnetic radiation, typically in the range from visible to infrared. We also acknowledge in-water or sub-sea acoustic sensing as a form of remote sensing but only briefly mention acoustics.

The remote sensing project (KMRP project 1.4) is specifically tasked with determining if there are cost effective options for utilizing remote sensing for assisting with long term Monitoring, Evaluation and Reporting (MER). MER of assets and values is important to managers who are responsible for knowing the state or condition of marine park assets, the pressures that impact them and for ensuring they are responding in an effective and efficient manner. Importantly, Project 1.4 needs to assess if remote sensing methods can deliver information on condition and pressure 'indicators' to construct time-series from historical and existing data and how data should be acquired going forward (with careful regard to state government cost and capacity limitations).

The specific objectives of Project 1.4

The specific objectives of Project 1.4 are:

- What existing data can be used to construct historical time-series of key biodiversity asset condition and pressure?
- What indicators of asset condition and pressure can be cost-effectively monitored by remote sensing?
- What methods and temporal and spatial scales are most appropriate?

This document is aligned specifically with the Kimberley, but the approaches, methods, findings etc. are likely applicable for other regions around Australia.

2. Environmental Monitoring and Management

Introduction

To answer the questions posed by the aims, we first need to identify the assets of interest, and the metrics currently used to measure/monitor the condition of the assets. Section 2.2 introduces the assets. Section 2.3 explains how DPaW manage the Kimberley, and explains the concept of condition, pressure and response with reference to monitoring and managing the state of the environment (assets), the approach adopted by DPaW. We surveyed DPaW to gather information on the assets of interest, and the metrics used to monitor condition and pressure, with the specific aim of identifying those which may potentially be monitored or measured by remote sensing methods. The metrics identified by DPaW are listed Table 4 in Section 2.3.2, below. Appendix 3 also provides some background to the DPaW asset survey results.

DPaW endeavour to collect data that provide relevant information on condition and pressure metrics. Remotely sensed data are currently utilized to address some needs, but there may be potential for these remote sensing technologies to support a wider range of needs. Also, the usefulness or accuracy of the data is dependent on factors such as sensor specifications, processing methods (algorithms), spatial and temporal resolutions. To address the second question, "what indicators of asset condition and pressure can be cost-effectively monitored by remote sensing", we need to determine the level of accuracy required for each metric, and the impact of different remote sensing data streams on the accuracy of the data, thus the third question, "what methods and temporal and spatial scales are most appropriate".

Section 3 presents a brief overview of some of the current and emerging capabilities of remote sensing, with specific reference to the metrics identified by DPaW as being of particular relevance. Some discussion of the limitations or accuracies of the remote sensing technologies is presented, as well as some comments on where there might be potential to either improve approaches, or adopt approaches to support some of the DPaW needs. Section 3 contains information on some archived data sets and sources of those data. Appendix 2 also contains potentially useful information on sources of remote sensing data.

DPaW Assets

Within the Kimberley, DPaW is the State agency tasked with management, monitoring and reporting of the environmental assets. To understand the metrics defined by DPaW in the assessment of assets, we first requested DPaW to identify the assets for the Kimberley region. These DPaW-defined assets are listed in Table 1. We then requested DPaW staff to fill in "Asset Spreadsheets" (see Figure A3.3 in Appendix 3). Table 2 shows an example of the feedback provided for the Coral Communities asset. The identified metrics were classified as potentially able to be measured/monitored/detected by remote sensing methods, or not.

Table 1. DPaW-defined assets.

Assets
Finfish
Coral
Seagrass
Invertebrates
Intertidal
Mangroves
Turtles
Cetaceans
Water Qualiity
Coastal Biological
Wilderness

Table 2. Example Condition/Pressure feedback for the Coral Communities asset.

Condition Metrics (followed through time)	RS possibility Y/N
C: Benthic cover	Y
C: Spp. Composition	N (general classification possible)
C: Diversity	N (depends on number of classes)
C: Size Frequency	N (depends on size)
C: Recruitment	N
Pressure Metrics (followed through time)	**RS possibility Y/N**
P: Temp (air and water)	Y
P: Cyclones	Y
P: Sedimentation	Y (estimates, surrogates possible)
Light Availability (Turbidity)	Y (via surrogates)
P: Predation	Broad scale impacts – Y
P: Vessel activity	Y (depends on spatial/temporal scale)
P: Acidification (long term need)	

As an example, for the asset "Coral communities", the Condition Metric "Benthic Cover" could potentially be monitored/mapped by remote sensing, but Recruitment was considered not able to be supported by the remote sensing technologies within the scope of this review.

With reference to pressure metrics, and again for the example of Coral communities, the Metric "Temperature", which included air and water temperature, could potentially be monitored by remote sensing methods.

An important point arising from the gathering of information from DPaW is that it is not a straightforward process to determine whether a metric can be measured/monitored by remote sensing technologies. Although we have assigned a Y or N in column 2 of Table 2, many of these could be argued, or needs to be justified or accepted with provisions, dependent upon such things as sensor specification, view conditions, and ecosystem parameters. Section 3 expands on this issue and presents comparisons of metrics and remote sensing technologies.

How DPaW manage the Kimberley

The management of the Kimberley marine parks is handled by DPaW. DPaW define a list of assets associated with the Kimberley marine environment (Table 1). In general terms, assets are biophysical constituents, the condition of which may be impacted by changes in pressures on the ecosystem. The management agency monitors the condition of assets, and the pressures on the assets, by measuring specific condition and pressure metrics. In certain circumstances DPaW may take various actions in response to changes in condition or pressure metrics.

2.1.1. Condition and Pressure Metrics

The Organisation for Economic Co-operation and Development (OECD) include monitoring and reporting on the state of the worlds environments within its purview. The OECD developed the Condition, Pressure, Response model for the reporting, and produced a report on key environmental indicators (OECD 2008)

The Australian and New Zealand Environment and Conservation Council (ANZECC) State of the Environment Reporting Task Force identified and developed a core set of environmental indicators applicable to national State of Environment reporting. This national reporting is a widely accepted process which aids environmental decision-making and enables assessment of progress towards ecological sustainability. There are seven broad themes encompassing the vast and diverse aspects of the Australian environments (Ward et al. 1998), one theme of which was referred to as Estuaries and the Sea but now is referred to as Coasts and Oceans. Table 3 lists the "issues" and "core indicators" within the Coasts and Oceans theme (ANZCCC 2000).

Table 3. Core State of Environment reporting environmental indicators for the Estuaries and the Sea theme (now referred to as the Coasts and Oceans theme).

Issue	Core Indicator
Marine Habitat and Biological Resources	Changes in coastal use
	Disturbance of marine habitat
	Total seafood catch
	Estimated wild fish stocks
Estuarine and Marine Water Quality	Coastal discharges
	Maritime pollution incidents
	Exceedences of marine and estuarine water quality guidelines
	Bio-accumulated pollutants
	Algal blooms in estuarine and marine environments
	Waste water treatment (coastal waters)
	Disturbance of potential acid sulfate soils
Global Processes	Sea level
	Sea surface temperature

Ward et al. (1998) were asked to recommend a comprehensive set of indicators, not constrained by current environmental monitoring. One consequence of this approach was that many recommendations were potentially not practical to implement in the short term. They were, however, a scientific basis for longer term planning of environmental monitoring and related activities.

One of the guiding principles for selection of the set of key indicators was that they must be the minimum set which, if properly monitored, will provide rigorous data describing the major trends in, and impacts on, Australian estuarine and marine ecosystems. The basis for selecting and defining the indicators was that they should include:

• indicators that describe the Condition of all important elements in each biological level in the main ecosystems;

• indicators of the extent of the major Pressures exerted on the elements; and

• indicators of Responses to either the Condition or changes in the Condition of the ecosystems and their elements.

The guidelines for development of the indicators were that each indicator should:

• serve as a robust indicator of environmental change;

• reflect a fundamental or highly valued aspect of the environment;

• be either national in scope or applicable to regional environmental issues of national significance;

• provide an early warning of potential problems;

• be capable of being monitored to provide statistically verifiable and reproducible data that show trends over time and, preferably, apply to a broad range of environmental regions;

• be scientifically credible;

• be easy to understand;

• be monitored regularly with relative ease;

• be cost-effective;

• have relevance to policy and management needs;

• contribute to monitoring of progress towards implementing commitments in nationally important environmental policies;

• where possible and appropriate, facilitate community involvement;

• contribute to the fulfilment of reporting obligations under international agreements;

• where possible and appropriate, use existing commercial and managerial indicators; and

• where possible and appropriate, be consistent and comparable with other countries' and State and Territory indicators.

2.1.2. DPaW Metrics

In a complex environmental system there are many factors (pressures) that influence the condition of assets. With consideration of the guidelines for selection of environmental indicators listed in Section 2.3.1, DPaW have identified the current metrics as relevant to providing useful information on the asset, and information that is measurable or able to be gathered efficiently.

Table 4 shows the Condition and Pressure metrics provided to this project by DPaW that have been identified as potentially able to be measured or monitored by remote sensing methods.

Table 4. DPaW-defined assets and associated Condition/Pressure metrics potentially able to be supported by remote sensing methods.

Asset	Condition metric	Pressure metric
Finfish Communities		Water Temperature
Coral Communities	Benthic Cover	Temperature (air & water), Cyclones, sedimentation, Turbidity, vessel activity
Seagrass Communities	Percent cover, Spp Composition, Spatial extent	Temperature (air & water), Cyclones, Sedimentation, sand movement, Light availability (turbidity), vessel activity
Invertebrate Communities		Cyclones, Sedimentation
Mangrove Communities	Spp. Composition, spatial extent, Canopy cover (density), Canopy height	Annual rainfall, Cyclones/storms, sea level rise, human activity
Intertidal Communities	Benthic cover, topography, diversity of habitats	sea level rise, Temperature (air & water), nutrient inputs, salinity, sedimentation, cyclones/storms, human use
Turtle Communities	Annual nesting abundance, sand temperature, air temperature, beach condition (habitat), in-water habitat (seagrass, reefs, soft bottom)	sand temperature, air temperature, cyclones/storms (beach condition), sea level rise, illegal access (vehicle tracks)
Water Quality	Sea surface temperature	turbidity (light attenuation), chl a (nutrient from anthropogenic influence - river outflow), rising sea level
Coastal Biological Communities	Spp. Composition, spatial extent, canopy cover, canopy height	annual rainfall, human activity, cyclones/storms, sea level rise

3. Remote Sensing

Aligning Remote Sensing and Condition and Pressure

Some metrics, the obvious one being sea surface temperature (SST) listed against the Water Quality asset, are directly available via remote sensing. In this case the remote sensing product is already being utilized by DPaW. However, temperature is also listed against assets such as Finfish, coral and seagrass. In these cases it is not necessarily SST, rather water column temperature, or temperature at the substrate, that directly impacts the asset. There is a strong correlation between SST and temperature at depth, but the two measurements are not necessarily exactly equal. In fact, the Group for High Resolution Sea Surface Temperature (GHRSST) (Donlon et al. 2007) define a sea surface "skin" (SST_{skin}), sub-skin ($SST_{sub\text{-}skin}$), bulk and foundation temperatures (SST_{fnd}). In this case remote sensing may not provide the exact metric, but can provide a highly correlated measurement.

Some metrics are not precisely defined, and the meaning of such might be interpreted differently by different science or management disciplines. Turbidity was identified as a metric against a number of assets, however on questioning the needs of DPaW in relation to turbidity, it was generally found that the turbidity was required to provide an estimate of how light conditions within the water column, or at the substrate, were changing. E.g. what is the average light available at the substrate for seagrass to photosynthesize, how often do light levels decrease below some pre-defined level? From the perspective of physical and optical measurements of water

column light fields, turbidity may be related to a number of other parameters, for example, scattering coefficients, light attenuation coefficients, light transmittance, and relationships to spectral and PAR measurements. Currently available remote sensing products do not include a turbidity product per se, but do include products that may be interpreted directly to help monitor light levels at the substrate. The remote sensing product "light attenuation at 490 nm" (K490, O'Reilly et al. 2000) is directly related to water turbidity and may be employed to estimate light levels at the substrate. Other remote sensing products such as Total Suspended Sediment (TSS), Chl-a concentration, spectral absorption and back-scattering coefficient, are all related to water turbidity and may help inform those interested in light levels at depth.

The task then is to understand the application or information required from the various metrics, and aim to identify remote sensing methods and products that either directly provide that metric, or related products that could potentially provide similarly useful information. Also, the level of resolution and accuracy required, and the limitations in remote sensing products need to be well defined.

An important aspect to consider is the "time span of interest". If the aim is to assess the current state of an asset then our interest is related to current technology and accuracy or relevance of a specific metric. The first question/aim, "What existing data can be used to construct historical time-series of key biodiversity asset condition and pressure", clearly defines an interest in time series of asset condition. Notwithstanding many issues related to data accuracy, spatial resolution and relevance, we need to consider the requirement to assess historical data and how far back in time are data available. Also, in relation to planned continuation of remote sensing monitoring, uptake of new and improved methods, or standardisation of approaches, how long can we expect the data supply to continue.

Potential for RS to service Management data needs

In assessing the metrics, or the needs of DPaW in relation to specific metrics and associated assets, and with respect to the potential for remote sensing science to support these needs, we have divided the metrics based on the physical principles of the remote sensing science. Thus, we consider metrics associated with atmospheric remote sensing, land surface remote sensing, water column properties, and mapping of shallow water substrates. The physical principles underlying the science that supports each of these four divisions may be considered quite distinct, thus the potential of each of these divisions, and the limitations of the current technologies, are potentially quite different.

3.1.1. Atmosphere

Atmospheric remote sensing works by detecting visible light scattered by air molecules and aerosols (dust, water droplets in clouds, and other small particles), or by infrared (thermal) radiation emitted from different layers of the atmosphere. The atmosphere may be considered as a many-layered structure that can vary rapidly through time but with properties that vary gradually over large horizontal scales. Thus, atmospheric remote sensing data are typically collected by geostationary satellites that view the earth every few hours, but at relatively low spatial resolutions of a few to tens of km (e.g. MTSAT, Meteosat, GOES and Feng Yun 2E and 2D). Polar orbiting sensors such as MODIS Aqua and Terra, NOAA AVHRR, and Feng Yun MVISR may also be employed to deliver atmospheric data, at a higher spatial resolution than the geostationary sensors, but typically only twice per day (day and night). Atmospheric remote sensing can also be carried out by ground-based sensors, such as dual-Doppler lidar to provide very high resolution near-surface wind fields (Stawiarski et al., 2013). In general terms, atmospheric remote sensing provides information on the 3 dimensional physical properties of the atmosphere, which in turn provide data used to describe and predict weather conditions.

The metrics able to be monitored by remote sensing methods are: Cyclones, storms, annual rainfall, and air temperature. All of these metrics are associated with data that can be provided directly from remote sensing instruments and are reasonably well accepted and well understood in terms of accuracy and confidence in the standard products.

The Bureau of Meteorology (www.bom.gov.au) provide access to near real time data as well as archived data. The metric annual rainfall is well defined and well understood, but the accuracy of the product, or the consequence of uncertainty associated with the product, from the perspective of DPaW, is not well defined. If the Bureau of Meteorology report rain gauge data for a specific location, the accuracy is very high, but if the annual rainfall for a location is inferred by interpolating gauge data from surrounding, and quite distant, locations and remotely sensed data are incorporated into the estimate as well, then the uncertainty is higher. Predicted rainfall, and in fact reported rainfall, does not incorporate the sometimes highly "patchy" spatial variability in rainfall amounts.

The metric "air temperature" is potentially able to be provided by remote sensing data, but for highly accurate data (tenths of a degree Celsius) at specific locations, *in situ* sensors are the best option. Remote sensing can provide estimates of air temperature, but the satellite-borne sensor "looks" through the atmosphere from space to earth's surface so, even after the complex data processing, does not provide a direct measurement of the air temperature at a specific height in the atmosphere, rather, it is an estimate of an integrated product over some number of km of the atmosphere near the earth's surface. Thus, we need to better define the DPaW-required accuracy of the air temperature, and the spatial scale or extent that air temperature is required. However, in terms of long-term archives and understanding annual and seasonal cycles at regional scales, remotely sensed air temperature is likely very useful for DPaW's needs.

The metrics "storms" and "cyclones", although well understood in terms of the physical phenomena, are not well defined in terms of the specific details of the metric requirements. It is possible to analyse BoM data to derive summary statistics such as mean wind speeds/directions (hourly, monthly, seasonal, annual), storm/cyclone intensity, duration, path, numbers of events per year etc.

There are some more specialized/advanced remote sensing instruments on orbit, and the future of weather monitoring and prediction is expected to be orders of magnitude better than current capabilities with the planned development of the Sounding and Tracking Observatory for Regional Meteorology (STORM) hyperspectral atmospheric sounding sensors by GeoMetWatch. However, for the current needs of DPaW the currently available data are assumed sufficient.

3.1.2. Land

The metrics potentially able to be supported by land-based remote sensing are species composition, spatial extent, canopy cover (density), canopy height, nesting abundance, sand temperature, and beach condition.

Species Composition, spatial extent and canopy cover (density): We may consider two main issues related to the ability of remote sensing instruments to measure or monitor vegetation metrics, spatial resolution and spectral resolution. Spatial resolution may be thought of as the size of the image pixel. A high spatial resolution sensor records data as a small pixel (cm to a few tens of meters), and low/moderate resolution sensors produce large pixels (hundreds to thousands of meters). A small image pixel can potentially contain information from a single object, such as a tree or bush, with potential to identify the object based on its spectral properties (colour). However, a large pixel may contain data associated with many objects, such as some coastal water, beach sand, bushes and trees all combined. It is unlikely that such a complex signal can be "unmixed" to identify the many constituents.

Spectral resolution may be described as the number of spectral bands, or channels, collected by the sensor. A common digital camera collects three bands, red, green and blue, and has low spectral resolution. A multispectral sensor collects many bands, typically with spectral gaps between some/all bands (e.g. MODIS collects 36 bands). A hyperspectral sensor, with high spectral resolution, collects an essentially continuous spectrum (e.g. Hyperion collects 220 contiguous bands from 0.4 μm to 2.5 μm) enabling processing using imaging spectroscopy methods. Spectral resolution is also a term applied to the width of individual spectral bands. In general terms, both aspects of spectral resolution impact the potential for habitat classification using remote sensing.

Moderate resolution sensors (e.g. MODIS, MERIS, AVHRR) cannot provide data at appropriate spatial resolution to identify species of vegetation or specific features at local scales, but there are numerous examples of large scale land cover coarse classification maps derived from these moderate resolutions sensors (e.g. Xie et al. 2008, and http://www.geo-informatie.nl/projects/pelcom/public/index.htm). High spatial resolution imaging sensors typically involve identification and classification based on spectral properties (colour) as well as form, shape and spatial relationships.

Field spectroscopy, a hand held hyperspectral remote sensing method, has demonstrated detectable and distinct spectral signatures for plant species studied (Ustin and Santos 2014, Sun et al. 2008), but the translation of the science to space-based remote sensing produces less reliable results (Xie et al. 2008). A review of remote sensing of vegetation by Xie et al. (2008) provides an excellent overview of the numerous technical issues affecting the ability to reliably distinguish vegetation classes using space-based remote sensing. Table 5 (Main features of image products from the different sensors) below is extracted from Xie et al. (2008) and represents a brief overview of the review. We will not elucidate all the technical issues here, but the final statement by Xie et al. (2008) is relevant; "Therefore, it is very preferable to conduct vegetation classification using the data acquired from the same sources and at the same period and applying the same processing methods for the entire region. The lack of such consistent and identical data (mainly remote sensed data and the reference data) for large regions often limits the production of vegetation maps with good quality.

There are some examples of airborne methods demonstrating varied levels of accuracy. For example, Engler et al. (2013) mapped 6 species of forest trees using combined airborne imagery (Airborne Digital Sensor ADS40-SH52) at 0.5 m resolution with a 12 class, 5x5 m map of topo-climatic conditions (e.g. slope, yearly solar radiation, soil water balance). Reported accuracy for the classification of 6 tree species ranged from about 48% to 86%. Engler et al. (2013) suggest improved results may be obtained by employing combinations of techniques such as pattern recognition techniques using object-oriented classification software such as eCognition, using lidar and multispectral, hyperspectral airborne data, and texture analysis of digital photography.

Patil et al. (2006) measured changes in distribution and abundance of two plant species using airborne 1 m resolution hyperspectral SpecTIR imagery. They compared the results of different spectral separation techniques (various forms of Spectral Angle Mapping) combined with supervised maximum likelihood classification. The 4 classes mapped were Saltcedar, Honey mesquite, grass, and agriculture. All 4 of the SAM approaches highlighted difficulties and issues with the data processing and map generation. The results suggest that it is difficult to develop a robust and repeatable data processing scheme which might be applied consistently to imagery through time, thus it is very difficult to effect confident change detection. It is interesting to note that they experienced difficulties in geolocating the 1 m resolution data. The raw navigation was estimated to be "out" by 15 m to 30 m. Registration with Quickbird imagery achieved a positional accuracy of around 2 to 3 pixels. Poor navigation confounds the potential to detect change in remote sensing data.

Wang and Christiano (2005) used QuickBird-2 data pan-sharpened to 0.6 m resolution to map salt marshes through time. They defined 3 categories, *Spartina* > 50% cover, *Spartina* 10% < 50% cover, and mudflats. This and other studies can be misleading in the statement that they map species of vegetation. In fact in this case a single species of grass was present, but named as a genus. Although it is true that a map is produced with genus named, it is not clear that the same genus could be mapped in the presence of other vegetation genera. In the salt marsh mapping, the only vegetation category is *Spartina* thus the mapping of vegetation versus mud is relatively simple compared to, for example, mapping *Spartina*, *Spinifex* and *Ammophila*, all genera of coastal grasses (if they were to occur together). For example, Ustin and Santos (2014) state, "Because Brazilian waterweed is most often found in monospecific stands and is the most abundant species in the Delta, any identification of submersed vegetation is likely to be Brazilian waterweed. Coontail is far less frequently observed and it often co-occurs intertwined with Brazilian waterweed, thus limiting our ability to identify it independently in the imagery". Nonetheless, Wang and Christiano (2005) report a validation accuracy of nearly 85% using the unsupervised classification protocol they developed based on the ISODATA (Iterative Self-Organizing Data Analysis Technique) approach. They suggest the digital image pixel-based processing is "better" than expert mapping by hand. The original manual mapping techniques had produced the classes *Spartina* greater than 50%, *Spartina* 10 – 50%, *Spartina* less than 10%, Mucky Peat, Mudflat, Interior, Mudflat Exterior, Tidal Creek, Pool, Sand, and Artifact and Sand Artifact. In fact, the automated protocol they developed mapped 5 classes, some which were agglomerations of some of the manual classes; the two *Spartina* classes, mud flat, high mud flat, and water. They conclude with the statement, "With comparable spatial resolution, the salt marsh information extracted from classification of Quickbird-2 images can be used for change detection against existing digital GIS format data derived from interpretation of aerial photographs. However validation and justification must be conducted when a comparison is to be done between data from different sources and using different methodologies. Details of digital satellite imagery data involved in change detection, such as minimum mapping unit, classification system, projection and registration, purpose of original map data, etc., need to be considered."

One of the strengths of remote sensing data is the long archive, particularly Landsat data. Cavanaugh et al. (2014) used 28 years of Landsat Thematic Mapper imagery to study changes in range and abundance and demonstrated a high correlation with a reduction in the frequency of cold events.

Mangroves along the western Australian coast often occur only along protected bays, however they can be impacted by major cyclonic events, storm surges, floods, and in the long term, sea level rise. Analysis of archival satellite images, pre and post major cyclone events will enable us to gain better understanding of the spatial variability of change due to these events, and to better understand recovery and its dynamics and contribute towards the understanding of future impacts under different environmental scenarios as well as potential geohazards such as surge waves associate with tsunami events.

Recent work along the eastern Exmouth Gulf (Paling, Kobryn and Humphries, 2008) utilised Landsat TM and airborne digital photography to study changes in mangal area over six years (1999-2004). A number of approaches to classification were employed, including ISODATA unsupervised classification, principal component analysis (PCA), calculation of normalised difference vegetation indices (NDVI), spectral and scatter plots, and visual interpretation. The classes mapped through time included for assessment of change detection included mangrove, saltmarsh, bare, water and dead mangrove. Metrics extracted from the time series imagery

included area, perimeter and perimeter to area ratio to evaluate patch fragmentation. Note the DPaW requirement to determine spatial extent of vegetation. There was an attempt to undertake an accuracy assessment using helicopter reconnaissance and comparisons with digital aerial photography. It is unclear what metric was assessed, but it appears that the accuracy of spatial extent was estimated to be 85 to 90%. The work showed that mangrove cover is very dynamic, partly due to regular cyclone events but also that recovery can be quite rapid.

A collaborative project between DEC (now DPaW) and DoF (Human et al. 2010) reports on remote sensing of mangrove to monitor spatial extent and condition. The report presents many useful insights and concludes, amongst other things, that higher spatial resolution is better for estimating extent of mangrove cover, particularly where vegetation is sparse or extent is at or around the pixel size of the imagery being utilised. Another finding was a need to collect ground-based measurements to calibrate the remote sensing imagery. The research included imagery from the Digital Multi-Spectal Imager (DMSI), Quickbird-2, and AVNIR-2 on ALOS. Discussion on the utility of the Landsat archive was also included. ALOS produces the most cost-relevant product for assessment by DPaW, being at a high enough resolution (pixel size 10 metres) to detect change in small/medium sized mangrove communities present in WA's marine parks. An important statement regarding Landsat for mangrove mapping was, "One satellite dataset currently available that fits the requirements of consistent imagery processed to a standard is the Department of Climate Change (DCC) annual continental coverage of Australia. As previously mentioned, Landsat has successfully been used to detect mangrove extent across the North West of Australia (Manson et al., 2001; Behn, 1999) however the 25m by 25m pixel size of the dataset preclude it from being an effective indicator of mangrove extent change in areas where the width of the mangrove stand is less than 50 m i.e. narrow fringing mangrove stands (Manson et al., 2001) and where the threshold of acceptable change is less than 25 m. Where large stands of mangroves exist and major impacts (anthropogenic or natural) influence mangrove distribution, Landsat is considered more appropriate for broad scale mangrove extent change detection and monitoring (Behn, 1999; Manson et al., 2001; and Paling et al., 2008)."

Schmidt (2003) suggests the "expensive and time consuming" aerial photography interpretation (API) produces a mapping accuracy of around 43%, whilst an expert system combining airborne hyperspectral data with terrain data derived from radar altimetry produces a vegetation map with an accuracy around 66%. The hyperspectal mapping alone produces a map with an accuracy of 40%. It is suggested that the expert system is an objective and repeatable method.

Ustin and Santos (2014) note the increased publication of hyperspectral techniques to detect and map vegetation, but state that even high spatial resolution remote sensing imagery has been insufficient to identify and map individual species. They review a number of factors limiting the performance and accuracy of remote sensing species mapping. They state "Yet, even with high resolution spectroscopy, mapping of individual species has been generally restricted to large monospecific vegetation patches, ecologically uniform conditions, homogeneous structure at the pixel resolution, or restricted to analysis of small datasets. Few studies have considered how species spectral identification changes with season, environmental conditions, and geographic locations. Even mapping large monotypic stands is challenging, unless the spectral properties of the species stand out from co-occurring species". They also discuss issues of spatial scale, field versus airborne spectroscopy, the use of field data to support image analysis, image calibration, and analytical tools. They conclude with the statement, "More research needs to be directed at determining the "right" spatial scale for spectroscopy measurements, particularly for IAS mapping. A geostatistical analysis of the spatial heterogeneity of the invasive species and the native plant background would provide the critical information needed *a priori* to determine the "best" spatial resolution. With more readily available high spatial resolution satellite data, e.g., GeoEye and Quickbird, perhaps some of the scale issues can be addressed using hyperspatial image data or even a creative use of Google Earth images."

Table 5. Some satellite-borne sensors that are used in environmental monitoring.

Products (sensors)	Features	Vegetation mapping applications
Landsat TM	Medium to coarse spatial resolution with multispectral data (120 m for thermal infrared band and 30 m for multispectral bands) from Landsat 4 and 5 (1982 to present). Each scene covers an area of 185 3 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level.
Landsat ETM+(Landsat 7)	Medium to coarse spatial resolution with multispectral data (15 m for panchromatic band, 60 m for thermal infrared and 30 m for multispectral bands) (1999 to present). Each scene covers an area of 185 km 3 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level or some dominant species can be possibly discriminated.
SPOT	A full range of medium spatial resolutions from 20 m down to 2.5 m, and SPOT VGT with coarse spatial resolution of 1 km. Each scene covers 60 3 60 km for HRV/HRVIR/HRG and 1000 3 1000 km (or 2000 3 2000 km) for VGT. SPOT 1, 2, 3, 4 and 5 were launched in the year of 1986, 1990, 1993, 1998 and 2002, respectively. SPOT 1 and 3 are not providing data now.	Regional scale usually capable of mapping vegetation at community level or species level or global/national/regional scale (from VGT) mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
MODIS	Low spatial resolution (250–1000 m) and multispectral data from the Terra Satellite (2000 to present) and Aqua Satellite (2002 to present). Revisit interval is around 1–2 days. Suitable for vegetation mapping at a large scale. The swath is 2330 km (cross track) by 10 km (along track at nadir).	Mapping at global, continental or national scale. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
AVHRR	1-km GSD with multispectral data from the NOAA satellite series (1980 to present). The approximate scene size is 2400 3 6400 km	Global, continental or national scale mapping. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
IKONOS	It collects high-resolution imagery at 1 m (panchromatic) and 4 m (multispectral bands, including red, green, blue and near infrared) resolution. The revisit rate is 3–5 days (off-nadir). The single scene is 11 x 11 km.	Local to regional scale vegetation mapping at species or community level or can be used to validate other classification result.
QuickBird	High resolution (2.4–0.6 m) and panchromatic and multispectral imagery from a constellation of spacecraft. Single scene area is 16.5 x 16.5 km. Revisit frequency is around 1–3.5 days depending on latitude.	Local to regional scale vegetation mapping at species or community level or used to validate vegetation cover extracted from other images.
ASTER	Medium spatial resolution (15–90 m) image with 14 spectral bands from the Terra Satellite (2000 to present). Visible to near-infrared bands have a spatial resolution of 15 m, 30 m for short wave infrared bands and 90 m for thermal infrared bands.	Regional to national scale vegetation mapping at species or community level.
AVIRIS	Airborne sensor collecting images with 224 spectral bands from visible, near infrared to short wave infrared. Depending on the satellite platforms and latitude of data collected, the spatial resolution ranges from meters to dozens of meters and the swath ranges from several kilometers to dozens of kilometers.	At local to regional scale usually capable of mapping vegetation at community level or species level. As images are carried out as one-time operations, data are not readily available as it is obtained on an 'as needs' basis.
Hyperion	It collects hyperspectral image with 220 bands ranging from visible to short wave infrared. The spatial resolution is 30 m. Data available since 2003.	At regional scale capable of mapping vegetation at community level or species level.

Murray et al. (2012) utilised the long archive of Landsat data to map the extent of tidal mudflats in China. Considering the spatial resolution of Landsat data (approximately 30 m pixels), this is only achievable where mud flats are extensive. As the spatial extent of a feature decreases in size, the relative accuracy of a mapped product decreases.

Baker-Gallegos et al. (2009) describe protocols for *in situ* monitoring of beach temperatures, and a case study in Costa Rica, to support monitoring of turtle nesting and incubation, but acknowledge the potential of some historical remote sensing data as useful for building the "temperature trend" for a beach of interest.

Combining data sources can potentially improve the classification accuracy. Fusion of data sources, such as lidar and airborne digital photography, has been shown to increase mapping accuracy of dunes and vegetation. Kempeneers et al. (2009) showed digital photography alone produced an accuracy of 55% whereas the combined data increased the accuracy to 71%.

Holmgren at el. (2008) report an accuracy for mapping trees into three species at 96% by combining airborne lidar and multi-spectral camera data. The lidar data is also able to provide information on delineation of tree crowns, tree crown extent, tree height and tree shape. Lidar can also provide data related to biomass, or leaf area index (LAI). The lidar and multi-spectral camera alone produced accuracies of approximately 88% and 84% respectively.

Chen et al. (2012) discuss processing methodologies that combine digital photography and lidar data to improve vegetation biomass estimation, stating an increase of the R2 parameter from 0.77 to 0.83 and a 10% decrease in RMSE when combining the two data sources. They also suggest the potential to extend this type of synergistic combination of high spatial resolution satellite imagery, digital image classification, and airborne lidar data to support more automated mapping of vegetation types, biomass and carbon.

The main points related to terrestrial mapping are;

- In general, higher spatial and spectral resolutions produce "better" results, but the actual sensor resolution necessary is very target specific.
- Change mapping requires careful consideration of repeatability and consistency of approach, including use of the same sensor (same spatial/spectral resolution), same data processing approaches, and same conditions (e.g. same season).
- Multi-sensor, multi-data or data fusion, including ground data for calibration, increases accuracy or product "quality" (e.g. spatial resolution, number of classes), as do methods involving expert interpretation.

3.1.3. Ocean

The metrics potentially able to be supported by ocean remote sensing include sea surface temperature (SST), turbidity, nutrient input, sea level rise, light availability, and sedimentation.

SST from remote sensing data is usually low resolution (1 km or lower) but daily. MODIS and AVHRR are the commonly utilised sensors providing free-to-ground data collected by Australian receiving stations (e.g. the Western Australian Satellite Technology Applications Consortium: WASTAC). Data are processed and made available in Australia by the Bureau of Meteorology, but are also available from NASA and NOAA in near-real time. Other sources of SST data include; National Climate Data Center quarter degree ~ 25 km at http://www.ncdc.noaa.gov/sst/; Coral Reef Watch half degree ~50 km resolution data http://coralreefwatch.noaa.gov/satellite/index.php with a reasonable description at http://coralreefwatch.noaa.gov/satellite/methodology/methodology.php; the Physical Oceanography DAAC at NASA's Jet Propulsion Laboratory (http://podaac-www.jpl.nasa.gov/). Long term studies of global scale events often utilise lower spatial/temporal resolution data. An example is Department of Fisheries reports by Caputi et al. (2010) and Pearce et al. (2011) where the source of SST is reported as the 1 degree (~100 km) resolution Reynolds SST data (Reynolds and Smith 1994) downloaded from ftp.emc.ncep.noaa.gov.

Remotely sensed SST has typically been accepted as accurate to about 0.5 degrees Celsius, but advances have been made to provide data with reported accuracies (when compared to *in situ* measurements) of about 0.3 degrees Celsius (GHRSST products). DPaW and DoF currently utilise NOAAA SST data, provided at approximately 9 km resolution (check this). The GHRISST products are probably the best and should be used.

Considering the points raised earlier in Section 3.2.1 regarding the various definitions of parameters used to describe ocean temperature, and accepting that each of these temperature values could be different by some

amount, of interest is the relationship between the satellite derived SST and the water temperature of interest to the researcher or monitoring agency. Smale and Wernberg (2009) compared *in situ* temperature logger data from about 10 to 12 m depth with AVHRR and MODIS-derived SST spanning two years for four locations in Western Australia. The AVHRR data appear to have been processed to 20 km spatial resolution, and the MODIS to 1 km resolution. Smale and Wernberg (2009) reported high correlation between the time series for the *in situ* versus remotely sensed data, but report differences of 1 to 2 C° between satellite and *in situ* temperatures. They suggest that the remotely sensed data are useful for detecting general patterns of ecological importance, but are not as supportive of remotely sensed SST for elucidating small scale variability. They "emphasize the need to carefully consider whether the accuracy and resolution of satellite-derived SSTs are appropriate for the specific ecological hypothesis being tested in nearshore subtidal habitats, and advocate the use of *in situ* loggers otherwise".

Pearce et al. (2006) studied the relationship between AVHRR-derived SST and data from *in situ* temperature loggers at Rottnest Island. The loggers were all deployed approximately in the top meter of coastal water. The level of pre-processing and quality control of the remotely sensed data appears to have been more stringent than reported by Smale and Wernberg (2009). They report 80% of the *in situ* temperatures were within ±0.5 C° and 95% within ±1.0 C°. They also point out the nominal uncertainty of temperature loggers as ±0.2 C°. Pearce et al. (2006) discuss the reasons for differences between remotely sensed and *in situ* measurements. In particular, satellite-based measurements are an "average" of a pixel (1km x 1 km) at a specific point in time, whereas the temperature logger delivers a measurement of the temperature at a precise location through time. Thus, diurnal cycles can bias the remote sensing data. Nonetheless, Pearce et al. (2006) report that the monthly mean temperatures of the remotely sensed SST and the logger data are within 0.3 C°. They conclude that remotely sensed data are adequate for studying the sea temperature climatology in near-shore waters, as long as navigation of pixels is managed carefully. Interestingly, they report problems with field work logistics, inclement weather and "inevitable loss" of loggers.

Analysis of time series, and spatial statistics, can provide useful insights into events and anomalies. An example of a significant event was the "marine heat wave" which occurred along the WA coast in 2011.

Wernberg et al. (2013) present work on the impact of the Western Australian marine heat wave of 2011. They present averaged *in situ* temperature logger data for two locations, but provide a region overview of the heat wave based on data provided by the National Weather Service and the NOAA Operational Model Archive Distribution Systems (NOMADS).

Smale and Wernberg (2012) report the impact of the WA marine heat wave, describing coral bleaching at the Houtman Abrolhos Islands. Water temperature is reported as based on remote sensing data. Observations of bleached coral, and other substrate types, were collected using an AUV.

Anomalous events can be detected and highlighted as "hotspots" in spatial maps of SST. One useful metric (among many) is "Degree Heating Days". Essentially a measure of the number of days above a specific threshold temperature, weighted by the degree by which the threshold is exceeded. Some of the background to anomaly detection using remote sensing is outlined by Maynard et al. (2007). The Bureau of Meteorology (BoM) currently provides a spatial SST anomaly 6 month forecast for the Great Barrier Reef [http://www.bom.gov.au/oceanography/oceantemp/GBR_SST.shtml]. The BoM also provides regional 7 days SST forecasts for 7 regions around the Australian mainland.

Andrews et al. (2014) study temperature sensitivity of seaweed and the effect on range reduction. They utilise and average temperatures collected by Tidbit temperature logger data collected from 2006 to 2010 at three locations within 1 to 3 km of their test sites. There certainly is potential to utilise the long archive of remotely sensed SST available to support similar studies.

Wernberg et al. (2011a) provide a review of the impacts of climate change and possible responses to these impacts. Bates et al. (2014) provide a comprehensive discussion on climate change on the range shifts in marine systems. An interesting point presented in Table 1 of Bates et al. (2014) that presents "usefulness of data to reconstructing historical species distributions", monitoring programs are considered robust, but are considered short term at typically less than 30 years. From the perspective of considering the potential of remote sensing archives to provide useful information, there are very few that extend back in time even by as much as 30 years. However, this does not negate the potential of remote sensing data to provide useful data that will, over time, grow to a long term archive.

An example of the use of SST at the ocean boundary is the work of Mazaris et al. (2009) who investigated changes in turtle population nesting phenology and report a correlation between SST in the foraging grounds, but state that the effect of SST in the foraging grounds on nesting is less important than the local conditions in the nesting ground. They utilised SST data from the Extended Reconstructed Sea Surface Temperatures,

version 3 (ERSST.v3; Smith et al., 2008). These data, including updated versions, are available from the Comprehensive Ocean–Atmosphere Data Set (COADS http://icoads.noaa.gov/.) and provide long-term monthly SST time series for the globe. ERSST.v3 data represent a validated reconstructed dataset of historical monthly SST based on *in situ* and satellite-derived observations at 2° global spatial resolution. The current COADS data extends back to 1800 at 2° global spatial resolution and at 1° resolution since 1960.

Considering that the beach temperature is more important than SST in foraging grounds, the potential for remote sensing to monitor beach temperature is of interest. Pendoley et al. (2014) present baseline data on the breeding of flatback turtles at 3 rookeries in the Pilbara region of Western Australia with some data extending over 6 breeding seasons. Temperature probes were deployed to measure nest temperatures. There is a comment on the width of beaches, suggesting one beach was 10 to 15 m wide, and the second was "narrow". This is relevant in terms of the potential of remote sensing to monitor such beaches. Certainly very high resolution commercial satellite sensors or airborne digital photography could provide sufficient spatial resolution to produce images of the beaches. However, temperature sensors are typically lower spatial resolution than visible sensors thus the potential of beach temperature monitoring by satellite remote sensing, particularly free-to-ground such as Landsat, is less likely. Of course if beaches are sufficiently wide, it might be that the larger scale temperature monitoring able to be provided by such sensors could provide useful information.

Pearce at al. (2006) reported reasonable results for remotely sensed temperature data close to the coast of Rottnest Island by careful analysis of surrounding pixels and temperature variability, but in general there are issues with SST close to coastlines and in narrow bays and estuaries, limiting the applicability of the medium resolution sensors to a few kilometres from the shoreline. High spatial resolution SST products may be derived from ASTER data and Landsat. Xing et al. (2006) describe a method to determine coastal water temperatures using Landsat-5 TM and Landsat-7 ETM data. Comparison with MODIS data showed an approximately 1 degree Celsius difference. The currently operational Landsat-8 would also be applicable. Fisher and Mustard (2004) used *in situ*-corrected SST from Landsat-5 and -7 to study long-term coastal water temperature climatologies. They state that, "this type of temporal data analysis is not a common application for high-resolution thermal data".

The suite of Landsat sensors through history have been designed, as the name suggests, for observing land. In terms of optical remote sensing, the ocean is extremely dark in comparison with the land, so the signal-to-noise level for Landsat data over the ocean is generally lower than over land targets. It is possible to "cross calibrate" satellite data with data from a "better" sensor, or one that has more stable calibration or a higher signal-to-noise ration. This approach can also be adopted for thermal sensors. Thomas et al. (2002) studied near-coastal SST using Landsat data archives from 1986 to 1996. The Landsat SST were calibrated by comparisons with AVHRR data. They conclude by suggesting, "An improved ability to quantify surface thermal variability in coastal regions at the time and space scales necessary to resolve relevant dynamics awaits the development and launch of a new earth observation mission. This mission will require radiometer characteristics capable of local atmospheric correction, at least the repeat/revisit cycle afforded by the NOAA satellite series coupled with a spatial resolution of order 100 m. Until such data are available, however, merging the optimal characteristics of AVHRR and Landsat offers one approach to bridging the current temporal/spatial gap in capabilities."

Fisher and Mustard (2004) propose using remote sensing data (Landsat) to interpolate *in situ* logger data, infilling the sparse *in situ* data and thus observing multiple scales of physical processes in coastal areas. They also conclude by saying, "We propose that the long history of the Landsat series satellites may be utilized to fill the data demand of local scale coastal and estuarine managers. This methodology offers the opportunity to tap into this wealth to generalize coastal processes and detect anomalous behaviour on a broad coastal scale".

Ocean colour remote sensing encompasses products derived by algorithms applied to spectral measurements in the visible region of the electromagnetic spectrum. Products typically include; Total Suspended Solids (TSS), chl-a concentration, attenuation of light at 490 nm (K490), spectral absorption and scattering coefficients, plus many more. Ocean colour sensors typically have a minimum set of wavelengths (IOCCG 2012) enabling a level of consistency between satellites. Some higher-resolution commercial sensors and Landsat have visible spectrum bands, although typically not complying with the minimum band set for true ocean colour sensors; thus they provide lower spectral resolution and quality.

In shallow waters and highly optically complex waters (e.g. river outflows, turbid dredge plumes), the "standard" algorithms employed for the majority of the polar orbiting earth observation satellites tend to fail in quantifying geophysical values, or at least provide skewed results. This does not preclude their use for detection of relative differences in indices of spatial features, such as algal blooms and river plumes. More recent global algorithms have improved these products to some degree, either by quantifying the Inherent Optical Properties (IOPs, i.e.

absorption and scattering coefficients) of seawater (e.g. GSM, QAA, GIOP, Maritorena et al. 2002, Leet et al. 2002, Werdell et al. 2013) or by using additional products for interpretation, such as fluorescence line height (FLH) (Blondeau-Patissier et al. 2014a). Blondeau-Patissier et al. (2014b) reviewed the advantages, limitations and challenges of bloom detection approaches in coastal waters, suggesting the current challenges are to overcome the severe limitations of these algorithms in coastal waters and refining detection limits in various oceanic and coastal environments. With regard to Australian waters, Blondeau-Patissier et al. (2011) analysed 10 years of ocean colour satellite data for phytoplankton blooms in the Broome, Great Barrier Reef (GBR), Perth, Tasmania and van Diemen Gulf areas. They acknowledge that the algorithm used for the studies typically provides Chl estimates with at best an error of 75%, but do use the results to report on relative spatial and temporal patterns. For example, results for the Broome area showed a peak of phytoplankton biomass in May, with high variability of blooms in August. The biomass showed a significant decline over the reported period of 2002-2010. Surface phytoplankton blooms occurred mainly in March and September. The data were used to estimate bloom coverage at less than 5% for the site. Approaches for detecting and mapping the presence of floating algal blooms have been reported. McKinna (2010) and McKinna et al. (2011) describe approaches to detect, classify and quantify Trichodesmium blooms within the GBR using MODIS data. Dekker et al. (2011) suggest it is feasible to detect floating algae along the Queensland coast using MODIS 250/500m by demonstrating the effect of producing false colour images with selected MODIS bands. A method to detect and map the spatial extent of floating algae using MODIS data has been reported by Garcia et al. (2013), including atmospheric correction, cloud detection, sun glint/illumination correction and definition of spatial extent.

Many regions of the Kimberley experience extreme tides, thus generating significant re-suspension of sediments, and heavy monsoon rains can lead to massive river flooding and extensive highly turbid river plumes. Also, when the water is clear, and tides are low, the substrate reflectance has an impact on the remote sensing reflectance, thus leading to poor results with the standard algorithms. Qin et al. (2007) demonstrated the poor operation of the standard algorithms in the Great Barrier Reef. Although there are recent advances in the processing of shallow water for MODIS data where the substrate is visible (McKinna et al.), there is still no robust method to consistently derive reliable estimates of bio-optical parameters in shallow and complex coastal environments such as often experienced in the Kimberley. Nonetheless, the recently launched eReefs water quality dashboard web site provides demonstration-quality marine water quality indicator products for management use by the Great Barrier Reef Marine Park Authority (GBRMPA) and Queensland State Government. The site also provides various SST products derived from the archive, such as SST Anomaly (SSTA), Degree Heating Days (DHD) and Mean Positive Summer Anomaly (MPSA) [http://www.bom.gov.au/marinewaterquality/].

Turbidity was discussed earlier. Issues with terminology related to turbidity and its relationship with water clarity, attenuation of light and light availability at the substrate were discussed in Section 3.1. Remote sensing does not provide turbidity per se, but many of the standard products may be useful either as surrogates for turbidity, or as useful tools in their own right. Turbidity is typically measured *in situ* by measuring (back) scattering of particulates. Remote sensing can provide estimates of scattering coefficients. Another measure related to turbidity is light attenuation. Remote sensing can provide estimates of light attenuation (e.g. K490 or derived from IOP estimates).

High resolution sensors may be more applicable to sedimentation, especially near the coast in shallow waters. Section 3.2.2 discusses land-based remote sensing, and in general higher resolution is better. Section 3.2.4 discuss shallow water substrate mapping and also suggests higher resolution is better. However, for high turbidity events the need to distinguish sharp boundaries between different classes, as in habitat mapping, is not necessarily required, and multi- and hyperspectral data are not necessary either. Sensors such as MODIS and MERIS can provide reasonable TSS estimates at a few hundred metres resolution, with archives extending back in time over many years (See Table A2 in Appendix 2). Landsat data can provide excellent estimates of TSS at high spatial resolution, with a very long archive available, but Landsat only collects imagery over the same region every 16 days and not all sensor wavelengths have remained consistent through the time series. Atmospheric correction is not as robust as for ocean colour sensors like MODIS and MERIS. Commercial high resolution sensors may be "tasked" to capture local regions, but are often expensive and again, typically do not have the spectral quality or resolution or length of time series that characterise ocean colour sensors. Long term archives of remote sensing data allow analysis of patterns and processes.

For SEWPaC (the Department of Sustainability, Environment, Water, Population and Communities) CSIRO performed a study on the use of systematic time series analysis of satellite images for the North Marine Bioregion where light attenuation and photosynthetic light availability at the benthos was calculated to function as a surrogate for biodiversity. The project reported bi-monthy averages of water quality parameters like chlorophyll concentration, TSS, coloured dissolved organic matter (CDOM) and SST to improve the understanding of up-welling currents and other sea surface phenomena.

Remote sensing data has the potential to provide maps of temporal and spatial extent of freshwater fluxes into the ocean using CDOM as a conservative tracer of freshwater. The CDOM can also be used as a proxy for salinity as CDOM is usually inversely related to salinity (Schroeder et al. 2012).

Section 3.2.2, Land, introduced the concept of multi-sensor approaches and the improved results derived from terrestrial mapping. A multi-sensor approach to environmental remote sensing of the ocean is discussed by Gade et al. (no date).

The main points are;

- Metrics such as turbidity *per se* are not delivered directly by remote sensing, but closely related products related to pigments (chlorophyll-a), suspended particulates (e.g. TSS), dissolved organics (CDOM) and light attenuation (Kd) can be used as proxies.
- Long archives of remote sensing data exist and can provide valuable insights into patterns and processes and various spatial scales. The archives are not yet long enough to support detection of "climate change" trends but can be used to investigate environmental and climate modes of variability (e.g. ENSO, IOD) and some human-use impacts.
- Adequate *in situ* data are necessary for deriving high-quality remotely sensed products. *In situ* data provide high confidence, but point measurements. Remote sensing data can be calibrated to *in situ* data to extrapolate spatially and temporally.
- Remotely sensed water column products are generally negatively impacted in shallow and coastal waters. Higher spatial resolution sensors can potentially deliver better products in coastal waters.

3.1.4. Substrate

The metrics potentially able to be supported by remote sensing technologies include <u>Benthic cover, Spp. Composition, diversity, spatial extent, and percent cover.</u>

At the national scale, Australia's coastal regions have been mapped into a spatial framework within the Integrated Marine and Coastal Regionalisation of Australia (IMCRA). The IMCRA classifies Australia's marine environment into bioregions that make sense ecologically and are at a scale useful for regional planning (Commonwealth of Australia ,2006). The framework is designed to be useful for subsequent finer levels of planning and management. The typical size of the IMCRA bioregions is many hundreds to thousands of kilometres.

The National Marine Bioregionalisation provides a picture of the spatial distribution of broadscale physical and biological components of Australia's marine jurisdiction. The shallow water habitats comprise only a tiny fraction of the total areas encompassed by the marine jurisdiction. Waters et al. (2010) discuss Australia's bioregionalisation and conclude with the view that marine biologists need to undertake quantitative analyses to test provincial biogeographic boundaries, rather than the current qualitative approach. There is potential for broad scale remote sensing to provide quantitative data on spatial extent of marine habitats.

Remote sensing scientists use the general term "shallow water mapping", or "shallow water habitat mapping". The range of remote sensing tools and data processing methods is rather broad. Many, if not all, of the sensors listed in Table 5 may be utilised to provide some degree of shallow water mapping capabilities. In general terms, "better" results are produced from sensors with higher spatial resolution (smaller image pixels) and/or higher spectral resolution (more spectral channels). Shallow water mapping may be carried out using satellite-borne sensors or airborne sensors (e.g. fixed-wing aircraft, helicopters or unmanned airborne vehicles [UAVs]). Due to the fact that airborne sensors are closer to the target (the earth's surface), the spatial resolution is typically much finer than space-borne sensors. Also, airborne sensors observe the target through maybe a few kilometres of atmosphere, whereas space-borne sensors observe the surface through hundreds of kilometres of atmosphere, an issue in terms of the approach to data processing. In general, "better" results may be derived from airborne sensors.

There are numerous examples of shallow water remote sensing in the literature, however it would not be fair to say that either satellite or airborne shallow water habitat mapping is well accepted as a consistent and reliable method. Also, it is not possible to accurately predict the quality or reliability of a map prior to data collection. Notwithstanding the impact of cloud, strong winds causing waves and whitecaps, or severe water turbidity, the final mapping result is also impacted by the spectral nature of the scene to be mapped. For example, mapping a region to three classes, where the classes comprise sand, one species of seagrass, and coral, will potentially produce a more reliable map than a region containing two species of seagrass and dark mud.

Discussions with potential end users typically suggest that higher spatial resolution maps are "better", but further analysis of specific needs suggests there is not a simple and unambiguous answer to the question of the best spatial resolution. In planning a mapping campaign, selection of spatial resolution would need to be carried out on a case-by-case basis. The same approach is also relevant in terms of the appropriate spectral resolution. The appropriate spectral resolution could be assessed on a case-by-case base, however there are not yet any reliable methods to accurately predict the level of classification, nor the accuracy of the classification, in any given mapping situation. These issues presuppose that the end user has the answers for what spatial resolution, what number of classes, and what accuracy is most appropriate!

Green et al. (2000), in their book "Remote Sensing Handbook for Tropical Coastal Management" provide many useful introductions and insights into numerous issues related to shallow water mapping (note: some of the specific information in the Handbook is becoming dated). It is not practical to review much of the content here, but scientists and managers new to the field of remote sensing would be well advised to become familiar with some of the content of the Handbook. Some of the topics discussed include cost benefits of different sensors and platforms, accuracy of different mapping methods, and time to process data.

Some examples of research are reported briefly below to provide an overview of the different sensors, the numbers and types of classes mapped, and some of the approaches and issues.

Phinn et al. (2008) studied satellite data from Quickbird-2 and Landsat-5 and airborne data from CASI-2, depths shallower than 3.0 m and state that mapping seagrass species (8 classes), cover (4 classes), and biomass (4 classes) to accuracies better than 80% was not possible across all image types. Airborne hyperspectral produced accuracies of 46%, followed by Quickbird-2 then Landsat-5. The gross finding was that higher spatial and spectral resolutions led to more reliable results.

Roelfsema et al. (2013) demonstrate mapping of reef systems using an object-based image classification of high spatial resolution (<10 m pixels) Quikbird-2 and IKONOS imagery. The classification process requires a set of contextual rules based on ecological and geomorphological principles, and potentially some level of user interaction, to arrive at a hierarchical map. The hierarchy of classes produced range from "land", "deep water" or "reef", through geomorphic classes such as inner or outer reef, to 7 classes of benthic community (e.g. sand, rubble, live coral, algae). The accuracy of the maps tend to range from relatively high for the initial classes ("land", "deep water" or "reef") and decrease in accuracy as the number of classes increases at lower levels in the hierarchy (benthic cover classes). Accuracies for geomorphic zones are reported as approximately 70-90% and benthic cover from 50-80%. In general, the object-based contextual mapping, including expert user interpretation, produces more classes and higher accuracy maps than a pixel based approach.

Roelfsema et al. (2013a) demonstrated mapping of seagrass in shallow water to assess <u>change in extent</u>. They showed that it is possible to produce maps of <u>change in seagrass extent</u>, but that a number of factors can lead to apparent change, including different sensor spatial resolutions, seasonal effects, water clarity, and different methods of collecting field data. Mapping and monitoring change using remote sensing methods must take into account such factors.

Phinn et al. (2005) report an approach to using Landsat 7 data to produce a combined <u>water quality</u> and <u>habitat map</u> which is tailored to the needs of an agency. The water quality is reported as secchi depth and habitat as three classes of seagrass cover.

Sanchirico and Mumby (2009) demonstrate a model to assess the value of mangroves, seagrass and reefs within the context of ecosystem services. They suggest that this improved understanding of the value of these coastal ecosystems may lead to different perspectives on coastal developments.

Wernberg et al. (2011b) studied the retreat of <u>seaweed extent</u> in response to climate change. They utilised three centuries of herbarium data, but point out that the volume of long term marine environmental data is particularly sparse. Certainly, the relatively short history of remote sensing technologies can not contribute, in a direct sense, to climate change studies. However, if managers and researchers form a long-term view of environmental management, it might be considered prudent to undertake a well formed plan of data collection and archiving, which remote sensing technologies could contribute to.

As mentioned briefly in Sections 3.2.1, 3.2.2 and 3.2.3, multi-sensor or multi-data approaches can improve quality or accuracy of remote sensing products. One aircraft can collect digital photography and Hyperspectral data contemporaneously. The digital photography is generally cheaper, but requires manual analysis to convert into a mapped product. Also, individual digital photographs often require navigation and "stitching". The hyperspectral data costs more to purchase due to higher instrument costs and some pre-processing undertaken by the provider. An experienced end user can potentially process the data in a semi-automated manner to develop a map. Geolocation to produce a large spatial coverage image or map is often "easier" than

managing a collection of individual single digital images. However, analysing both data sets could improve the products.

The main points of note;

- Better spatial resolution, and better spectral resolution tend to increase the likelihood of deriving more classes in a habitat map.
- Higher spatial resolution sensors can potentially deliver more accurate estimates of spatial extent, and spatial change.
- Methods need to be repeatable if results are to be used for long term monitoring and change detection.
- The same issues as outlined in the terrestrial mapping are relevant here, specifically change mapping requires careful consideration of repeatability and consistency of approach, including use of the same sensor (same spatial/spectral resolution), same data processing approaches, and same conditions (e.g. same season).
- Processing involving approaches such as contextual mapping, expert user input, and interactive interpretation tend to provide more reliable and higher order maps than fully automated pixel based processing with limited user interpretation.

3.1.5. Acoustics

Although this review does not focus on acoustics, it is worth noting the potential, and as mentioned in the terrestrial mapping discussion earlier, improvements in habitat and ecosystem mapping could potentially be gained by fusion of different data streams, such as visible (satellite or airborne) and acoustic data.

Most active acoustic remote sensing is in the form of echo-sounder surveys to produce charts. Charts are available for the whole of the Kimberley region. For instance, there are geo-referenced charts in a *.tif format, called Seafarer, available from the Hydrographic Office: http://www.hydro.gov.au/seafarer/geotiff/geotiff.htm. However, the resolution and format of hydrographic charts does not always lend itself well to scientific studies. Geoscience Australia (GA) has a 200 m bathymetric and topographic grid of Australia, which is supplied in more user friendly formats: https://www.ga.gov.au/products/servlet/controller?event=GEOCAT_DETAILS&catno=67703

Where acoustic backscatter data has been collected by echo sounders and sonar systems, data can be used to infer seafloor and water column properties. Seafloor backscatter data can be used for habitat mapping such as discriminating between substrates and identify the presence of marine vegetation. Acoustic backscatter data from the water column can be used to assess the distribution of biomass, including the discrimination between fish and plankton as well as be used to observe oceanographic features such as internal waves and fronts.

Passive acoustic remote sensing generally is carried out through the deployment of sea noise loggers. Sea noise loggers have been deployed in various locations in the Kimberley over at least the last 10 years. Sea noise data has been used to examine marine fauna (mainly marine mammals), industrial noise sources and the interaction between them.

4. Conclusions

The previous sections outline the current uses of remote sensing for environmental monitoring of the atmosphere, land, water column and substrates. Examples have been provided to indicate the breadth of applicability, limits of accuracy, and what some of the specific issues are. We discuss here the main points with reference to the metrics and assets identified by DPaW (see Table 4).

Remote sensing, as with all measurement methods, has benefits and limitations. We can define the limitations to some degree (such as spatial resolution, or precision of products), but others depend a lot on the viewing conditions, or the scene being studied. For example, if all the classes in a shallow coastal region are very distinct, such as rock, coral, algae and seagrass, then we can distinguish a lot of classes with high confidence, but if they are all similar, such as five types of coral, then we can't easily classify them.

Condition metrics

For the assets Coral, Seagrass, Mangrove, Intertidal, Turtle and Coastal Biological Communities, the condition metrics listed in Table 4 are nearly all characteristics that require, or benefit from, high spatial resolution information. All of these assets are either shallow water substrates (Section 3.2.4) or land-based (Section 3.2.2). The two condition metrics that are not substrate or land are the condition metrics SST, listed against the asset Water Quality, and air temperature, listed against turtle communities. Water column properties were discussed in Section 3.2.3, where it was shown that the spatial resolution is typically lower than required for the substrate and land mapping. Notwithstanding the need to determine SST within about a km of the shore, or in narrow estuaries, embayments or river mouths, SST is relatively well established as a remote sensing product with quite predictable characteristics in terms of accuracy and confidence. In contrast, the accuracy or confidence in the substrate and land products can vary quite dramatically, depending on the region or habitat type to be mapped. The condition metric, air temperature, was discussed in Section 3.2.1. For the accuracy and spatial scale required for determining local conditions at turtle nesting beaches it is likely that remotely sensed air temperature may not be accurate enough. For high spatial resolution, accurate data, and inclusion of diurnal cycles, *in situ* temperature sensors are the best method.

For the condition metrics benthic cover (coral and intertidal communities), percent cover (seagrass), spatial extent (seagrass, mangrove and coastal biological communities), and in-water habitat (turtles), the main approach to deriving these metrics is simply image processing to determine edges or boundaries of features to determine spatial coverage. If the features or boundaries are well defined then the prime factor determining quality of the mapped product or accuracy of products is the spatial resolution of the sensor. In general, airborne sensors provide higher resolution than satellite sensors. "Standard" digital photography can often provide higher resolution than "advanced" sensors (e.g. hyperspectral scanners), however processing of digital photography often includes complications of navigation and potentially laborious human interpretation methods.

Digital photography with human interpretation is well suited to monitoring the condition metric "beach condition" for turtle communities. Depending on the spatial coverage and frequency of monitoring, either airborne or "cameras on poles" would be appropriate. The description of beach condition has not been well defined. If this includes features such as beach slope and shape then airborne lidar may also be appropriate for larger surveys. Although we did not find examples of remote sensing for nesting abundance, digital photography is unlikely to be appropriate for monitoring annual nesting abundance (turtle communities) if the nesting activity occurs at night. Infrared or low-light cameras may be useful, possibly mounted on poles during nesting seasons. Human interpretation is probably required to process the imagery initially, however automated processing could be developed to analyse time series imagery of fixed locations.

For the condition metrics species composition (seagrass, mangrove, coastal biological communities), diversity of habitats (intertidal communities), and in-water habitat (turtles), either more advanced sensors (multispectral or hyperspectral), and/or more advanced or complicated processing methods are required (spectral/texture/shape analysis, contextual analsysis, supervised classification, human interpretation). These remote sensing products may be considered "in development", with most examples in the literature presented as proof of concept or new approaches. Certainly, the methods are not well established or widely accepted as standard. Many remote sensing-derived maps include species names, however the ability to identify a species in the absence of an "expert user" providing the classification is likely not possible in an automated sense. Also, identifying a single species in the presence of highly contrasting neighbours is probably relatively simple, however this cannot be regarded as species identification. However, improvements in data processing continue to be made, as well as improvements in the technical specifications of the instruments. Also, new hybrid multi-

sensor methods are proving to deliver more robust results. The quality of the derived products is difficult to predict and is highly dependent on the features being mapped.

The condition metrics canopy cover (mangrove, coastal biological communities) and canopy height (mangrove, coastal biological communities) are both quite structural and probably more aligned with lidar monitoring methods.

A key issue to evolve from the earlier review of literature was the accuracy of change detection. As previously stated, the substrate and land metrics are all require, or benefit from, high spatial resolution image data. Higher spatial resolution data can be adversely affected by poor navigation, which has a significant negative impact on change detection. Also, considering the non-standardised approaches, rapidly changing (improving) methods and technologies, users need to be aware of the impact on change detection using remotely sensed data.

Also, users need to be aware of the way products are reported. Large numbers of habitat classes does not imply more accurate or better processing methods. In fact, it is quite easy to produce a product that "looks nice". Users need to question the data quality, processing methods, and instrument calibration. One of the best tests, apart from *in situ* validation, is to ask for examples through time to prove that results are stable.

Pressure metrics

In contrast to the condition metrics listed in Table 4, the pressure metrics tend to be represented by generally lower spatial resolution environmental parameters, and more parameters that relate to weather conditions. As discussed in Section 3.2.1, many of the remotely sensed atmospheric products are well established and well understood. Data are generally freely available from the BoM.

The pressure metrics air and water temperature, cyclones/storms, and annual rainfall are listed against the assets, finfish, coral, seagrass, invertebrates, intertidal, turtles and coastal biological communities. Although in a few cases, such as related to monitoring the pressure of air temperature on the Turtles asset, higher spatial resolution data are probably more appropriate, the standard products from the BoM are useful. Of interest to DPaW are statistics related to these metrics, derived over varying periods of time, such as annual totals (e.g. rainfall), annual/seasonal variability including max/min/mean (e.g. air temperature), and frequency (e.g. cyclones/storms).

The pressure metrics water temperature, turbidity, light availability and chl *a* are listed against the assets finfish, coral, seagrass, invertebrate, intertidal, and water quality. Some of these pressure metrics are considered reasonably well established remote sensing products, although there are limits on the accuracy or availability of products in certain environmental conditions or locations. Unfortunately these locations tend to be in shallow waters and very close to coastlines or emergent reefs. Section 3.2.3 discussed ocean remote sensing. For regional perspectives and long term climate-related studies, the moderate to low resolution (one to a few km resolution) data are adequate. There are examples of advanced processing methods to overcome some of the limitations of near-shore monitoring, and examples of high spatial resolution products derived from sensors such as Landsat or high spatial resolution commercial sensors.

As was discussed for the weather-related metrics, DPaW have an interest in spatiotemporal statistics to describe baseline conditions, and deviations from "normal" annual or seasonal conditions. Considering the availability of long-time-series archives, it is possible to derive maps of extreme deviations, described as "hotpsots". These hotspot maps can help identify locations, intensity and duration of pressures impacting assets. Specifically, hotspots for ocean temperature pressure metrics are useful for finfish, coral, seagrass and intertidal communities. Hotspots for turbidity (events of extreme turbidity) are useful for identifying increased pressure on coral and seagrass communities as well as water quality. It is important to note that turbidity is very much an *in situ* metric, and remote sensing can't easily measure this (see Section 3.2.3), but there are other products that could be adopted (e.g. K490 or scattering coefficients).

The coral, seagrass, invertebrate, and intertidal communities all list sedimentation as a pressure metric. Intertidal communities also list nutrient inputs and salinity. These metrics can all be considered as derived products based on other directly measured water column properties. There may be a need to include interpretation of a series of images, or derivation of products based on modelling. For example, remote sensing can provide reasonable estimates of TSS, however to determine sedimentation requires knowledge of factors such as ocean currents, turbulence, particle size, and particle density. Ocean salinity can be measured using microwave sensors, and improved products derived by including measurements ocean colour and ocean temperature, but the derived products are at spatial resolutions of more than 100 km. Salinity associated with

tracking fresh water outflows from rivers can be inferred by interpreting images of plumes, either TSS or coloured dissolved organic matter (CDOM). However, accurate measures of salinity require *in situ* sensors.

Sea level rise is a pressure metric that is potentially able to be monitored by remote sensing methods. This was not discussed earlier. The current technology, on board the Jason-1 and Jason 2 satellites, relies on an active sensor, whereby a radar signal originating at the satellite-borne sensor is directed at the ocean surface and reflected back to the sensor. The satellite altimeters can measure sea surface height to accuracies of about 3 cm. If the DPaW need is to monitor high sea level events, then an altimeter could prove useful. However, if the interest is sea level rise in the longer term then it is likely that longer term records from tide gauges may be more appropriate.

High spatial resolution imagery, including airborne digital photography, may be employed to monitor the pressure metrics vessel activity (coral and seagrass communities), illegal access/vehicle tracks (turtle communities) and human use/activity (mangrove, turtle and coastal biological communities). Very high spatial resolution sensors are required to identify features such as vehicle tracks, camp sites, motor bikes, small boats etc. The frequency of monitoring is an issue. If daily monitoring is to be achieved, there are no low cost (free) high spatial resolution sensors available that can deliver daily imagery. It should be noted that the Deimos-1 satellite, operated by Deimos Imaging, can provide 22 m resolution imagery at relatively low cost (a few hundreds of dollars) with tasking capabilities. High resolution imagery may also be applicable to monitoring sand movement, either by direct observation and interpretation of a series of images, or by advanced processing of hyperspectral data to derive water depth through a series of images, or by flying an aircraft with water-penetrating lidar capabilities to measure water depth directly.

We still need more information on how accurately some metrics are required. A specific example is beach temperature to support the turtle asset. It is likely that remote sensing can provide beach temperature, but it is unlikely that data can be provided at the accuracy and resolution of current *in situ* methods. An analysis of *in situ* versus remote sensing data with respect to impacts on turtle breeding, habits etc. may be enlightening. A brief review of the size of the few known turtle nesting beaches in the Kimberly suggests they are a few tens of metres wide. Standard Landsat data at 30 m resolution can be pan-sharpened to 15 m for mapping beach extent, but the 100 m resolution thermal sensors would not have the resolution to measure beach temperature with sufficient accuracy.

5. Gaps and direction for further work

Section 3, above, provided an overview of issues related to accuracy and applicability of remote sensing to environmental monitoring. One of the key points to emerge from the review is the issue of change detection, and the need to understand the impact of different spatial resolution, processing methods and environmental conditions on the accuracy of the change detection.

Section 4 discussed the condition and pressure metrics associated with each of the assets defined by DPaW. The condition metrics tend to be high spatial resolution in nature and therefore require sensors with resolutions in the range of metres to possibly a few tens of metres, depending on the asset to be mapped or monitored. The literature certainly makes the point about taking care when attempting to monitor change, and also suggests that the accuracy of products is scene or situation dependent. This means there is little or no advice on the potential accuracy or applicability of different sensors or processing methods for specific mapping or monitoring requirements in the Kimberley. Thus there is a need, and an opportunity, to undertake work to compare and contrast different approaches to monitoring change in assets, condition and pressure metrics in the Kimberley.

Issues to consider when determining priorities for research and development include:

- Observe the guidelines introduced in Section 2.3.1 for the development of environmental indicators.
- Select mapping and monitoring activities that are aligned with the needs of DPaW (condition and pressure metrics in Table 4). Survey results (Appendix 3) indicate Temperature and Turbidity are the two metrics with the highest frequency of response.
- Select mapping and monitoring activities that are relatively cost effective for the quality of product. For example, can Landsat or Deimos sensors provide useful reef maps compared to maps derived from airborne digital photography or hyperspectral sensing?
- Can the quality of hotspot data be improved by using GHRSST products, higher spatial resolution data, or advanced processing methods to derive TSS data?

- Landsat data are currently utilised for various mapping purposes. Can the same data sets be processed to derive new products, such as near-shore SST or TSS? What *in situ* data might be available or would be needed to calibrate the Landsat products?
- Atmospheric correction for high resolution sensors such as Landsat is not as robust as for coarser resolution ocean sensors that provide well validated geophysical products at the global scale. Can the consistency of atmospheric correction, hence data quality, be improved by combining the spectral and spatial resolutions of these different types of sensors in a merged product?
- Are "standard" MODIS/MERIS water column products (K490, scattering) correlated with *in situ* turbidity data? Would these products satisfy the needs of DPaW.
- Is there a baseline record/map/data to assess change against? For example, is there a current map of beaches and tidal mudflats for the Kimberley?
- With respect to land mapping, possibly the simplest asset to map is mangrove, with spatial extent the most straight forward condition metric to produce. Considering the spatial extent of mangroves, from hundreds of metres to single plants, what proportion of mangroves, can be adequately mapped with current methods, and how sensitive are these methods to change? Can the mapping be improved with little increase in cost? Is there a good baseline map of all mangroves, or just selected regions?
- What data sets already exist for undertaking comparative studies? There are airborne digital photography, hyperspectral, commercial high resolution, and Landsat data available for regions such as Montgomery Reef, as well as freely available data with broadscale coverage (e.g. MODIS).
- Development of remote sensing products and derivatives such as hotspots, data processing, mapping approaches etc. need to consider factors such as the long term application in terms of stability, repeatability, robustness, applicability to different sensors, and transferability to different locations. Which existing datasets provide self-consistent time series of sufficient duration to characterise baseline natural variability and enable change detection? How likely are these to continue into the future?

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7. Appendices

Appendix 1

Extracted from the REMOTE SENSING Handbook for Tropical Coastal Management (Green et al. 2000), the Executive Summary.

Guidelines for Busy Decision Makers

Executive summary

The purpose of this *Handbook* is to enhance the effectiveness of remote sensing as a tool in coastal resources assessment and management in tropical countries by promoting more informed, appropriate and cost-effective use.

1.A primary objective of the

Handbook is to evaluate the cost-effectiveness (in terms of accuracy of resource estimates or habitat maps) of a range of commonly used remote sensing technologies at achieving objectives identified by the user community. The research activities reported were focused on the Turks and Caicos Islands with comparative work in Belize but outputs are seen as applicable in all countries where water clarity permits optical remote sensing.

2. Sensor technologies evaluated included: Landsat Multispectral Scanner (MSS),Landsat Thematic Mapper (TM), both multispectral (XS) and panchromatic (Pan) SPOT High Resolution Visible, Compact Airborne Spectrographic Imager (CASI) and aerial photographs. Spatial resolution of the digital imagery ranged from 1–80 m, and spectral resolution from 1–16 wavebands in the visibleandinfra-red.3.For habitat mapping, which is the primary objective of users, the achievable accuracy of outputs depends on: i) the level of habitat discrimination required, ii) the type of sensor used, iii) the amount of ground-survey carried out, and iv) the image processing techniques used. Accuracies of outputs are evaluated for different levels of marine or mangrove habitat discrimination for each sensor with varying ground-survey and image processing inputs (costs).

4. Satellite-mounted sensors are only able to provide information on reef geomorphology and broad scale ecological information such as the location of coral, sand, algal and seagrass habitats with an accuracy ranging from 55–70%. For this type of information, the most cost-effective satellite sensors for habitat mapping are Landsat TM (for areas greater than one 60 x 60 km SPOT scene) and SPOT XS for areas within a single SPOT scene. Both these sensors can deliver overall accuracies of about 70%. The remaining satellite sensors tested (SPOT Pan and Landsat MSS)could not achieve 60% overall accuracy even for coarse-level (only 4 marine habitat classes being distinguished) habitat discrimination.

5.For fine-scale habitat mapping (9+ habitat classes) only colour aerial photography and airborne multi-spectral digital sensors offer adequate accuracy (around 60% or better overall accuracy). The most accurate means of making detailed reef or mangrove habitat maps involves use of digital airborne multi-spectral instruments such asCASI (Compact Airborne Spectrographic Imager).

6. Using CASI we were able to map sub-littoral marine habitats to a fine level of discrimination with an accuracy of over 80% (compared to less than 37% for satellite sensors and about 57% for colour aerial photography). Similar accuracy was achieved for mangrove habitats using CASI. Comparison of the costs of using CASI and colour aerial photography indicates that CASI is cheaper as well as producing more accurate results.

7. Additional field studies were carried out of the capabilities of remote sensing to map bathymetry and assess mangrove resources (Leaf Area Index (LAI) and percentage canopy closure) and seagrass standing crop (g.m-2). Remote sensing offers very cost-effective rapid assessment of the status of the plant resources but passive optical remote sensing of bathymetry is considered too inaccurate for most practical purposes. The practicalities of using remote sensing technologies for i) coastal resources (fisheries, conch (*Strombus gigas*), *Trochus*, and seaweed resources)assessment, and ii) monitoring of coastal water quality (including sediment loadings, oil, thermal discharges, toxic algal blooms, eutrophication and other pollution) are reviewed.

Appendix 2

Table A2 contains an overview of various remote sensing platforms/sensors, technical specifications and information regarding data archives.

				GEOSTATIONARY				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**
GMS	Vis and thermal IR	2 to 4 bands	1.25 km (VIS) 5 KM (IR)	4 hour to 1 hour	lots	1979 - 1995	Available	BoM cost recovery
MTSAT (1R and 2)	Vis and thermal IR	5	1 km (VIS) 4 KM (IR)	1 hour	lots	1995 - current	Available	BoM cost recovery
				MODERATE RESOLUTION POLAR ORBITORS				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**
MODIS	~400 - 12500 nm	36	250, 500, 1000 m at nadir	~ 4 times a day	35200	24/02/2000 - current	Available	free
VIIRS	~400 - 12500 nm	22	375, 750 m at nadir	2 times a day	unknown	2012 -	Available	free
MERIS	~390 - 1040 nm	15	300, 1200 m at nadir	1 - 3 days	unknown	Mar 2002 - current	Available	free (I think)
SeaWiFS	~402 - 855 nm	8	1.1 - 4.4 km	1 day	unknown	Mid 1997 - 2006	Available	free
AVHRR	~580 - 12500 nm	5	1km	2 times a day	lots	1990 - ?	Available	free
Landsat (1 - 8)	~400 - 12500 nm	8	15, 30, 60, 120 m at nadir	16 days	unknown	07/1972 - current	Available	free
CZCS	~443 - 750 nm	5	825 m at nadir	not consistant	unknown	06/1978 - 10/1986	Available	free
ALI	PAN, VIS/NIR	10	10, 30	16	unknown	2001 - current	Available	free
DEIMOS	~520 - 900 nm	3	22m	2 -3 days	tasked, archive-unknown	July 2009 - current	Available	~$0.08 USD sq km
AVNIR-2	~420-890 nm	4	10m	1 - 2 days	unknown	Jan 2006 - Apr 2011	unknown	unknown
ASTER	Green, Red, NIR, SWIR, Thermal	5	15 m, 30 m, 90 m	4 - 16 days	unknown	Feb 2000 - current	unknown	unknown
				HIGH RESOLUTION POLAR ORBITORS				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost (archive data)**
Worldview II	~396 - 1043 nm	8 + pan	0.5m pan, 2.0m multi	1.1 - 3.7 days	tasked, archived-unknown	Oct 2009 - current	Available	~$16.00 USD sq km
SPOT 1 - 7	~450 - 1750 nm	3 & 4 + pan	2.2m - 10m pan, 8.8m - 20m multi	1 - 5 days	tasked, archived-unknown	Feb 1986 - current (5 -7) (1 - 4 not operational)	Available	~$5.15 USD sq km
IKONOS	~445 - 853 nm	4 + pan	0.82 m pan, 3.2 m multi	3 - 5 days	tasked, archived-unknown	Sept 1999 - current	Available	~$10.00 USD sq km

GeoEye	~450 - 920 nm	4 + pan	0.5 m pan, 2.0 m multi	2.1 - 8.3 days	tasked, archived-unknown	Sept 2008 - current	Available	~$16.00 USD sq km
QuickBird	~405 - 918 nm	4 + pan	0.61 m pan, 2.4 m multi	2.4 - 5.6 days	tasked, archived-unknown	Oct 2008 - current	Available	~$16.00 USD sq km
RapidEye	~440 - 850 nm	5	6.5m	1 day	tasked, archived-unknown	Aug 2008 - current	Available	~$1.28 USD sq km
Pleiades	~430 - 940 nm	4 + pan	0.7m pan, 2.8m multi	1 - 13 days	tasked, archived-unknown	Dec 2011 - current	Available	~$13.00 USD sq km
KOMPSAT-3	~450 - 900 nm	4 + pan	0.7m pan, 2.8m multi	1.4 - 4.1 days	tasked, archived-unknown	May 2012 - current	Available	~$8.00 USD sq km
Worldview I	N/A	pan only	0.5 m	1.7 - 5.4 days	tasked, archived-unknown	Sept 2007 - current	Available	~$13.00 USD sq km
				HYPERSPECTRAL SATELLITES				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**
Hyperion	~400 - 2550nm	172 useful	30 m at nadir	16	46, 8 Coastal or marine	20/06/2001 - 31/12/2010 (other data still being produced)	Available	free
HICO	~400 - 900 nm	87	90 m	~ 3 days	unknown	Sept 2009 - current	Available	free
AIRS	Thermal IR sounder	2378	13.5 km	0.5 days	unknown	May 2002 - current	Available	free
IASI	Thermal IR sounder	8461	12 km	daily (probably)	unknown	2006 - current	not known	not known
				AIRBORNE HYPERSPECTRAL				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**
HyMAP								
Eagle								
Hawk								
HySPEX								
				AIRBORNE LIDAR				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**
RIEGL								
				RADAR				
Sensor	**Bandwidth**	**No Bands**	**Spatial Resolution**	**Revisit time**	**Approximate number of scenes**	**Dates of the Archive**	**Availability**	**Cost**

Appendix 3

A survey was conducted of current and potential users of remote sensing technologies who are associated either through management or research with the marine and coastal environments of the Kimberley region. These end-users were surveyed using specific written questionnaires, by phone or face-to-face interview, or in small groups. The results of the surveys were presented at a workshop held on 19th August 2013 where participants were invited to discuss the issues and provide feedback on the development of the project. Table A3 lists the survey participants.

This appendix presents an overview of the results of the surveys in graphical form.

Table A3.1 People surveyed as part of the KMRP, Project 1.4

Participant	Affiliation		E-mail
Alan Pearce	DoF	Res	Alan.Pearce@fish.wa.gov.au
Alison McCarthy	DPaW	Man	Alison.McCarthy@DPaW.wa.gov.au
Andre Bobojcov	DPaW	Man	Andre.Bobojcov@DPaW.wa.gov.au
Ben Hebiton	DoF	?	Ben.hebiton@fish.wa.gov.au
Christopher Nutt	DPaW	Man	Christopher.Nutt@DPaW.wa.gov.au
Corey Wakefield	DoF	Res	Corey.wakefield@fish.wa.gov.au
Daniel Gaughan	DoF	Res	Daniel.Gaughan@fish.wa.gov.au
Darren Stevens	DPaW	Man	Darren.Stevens@DPaW.wa.gov.au
Gary Jackson	DoF	Res	Gary.jackson@fish.wa.gov.au
George Shedrawi	DPaW	Res	George.Shedrawi@DPaW.wa.gov.au
Jeff Norris	DoF	Res	Jeffrey.norriss@fish.wa.gov.au
Jim Greenwood	CSIRO	Res	Jim.Greenwood@csiro.au
Kathy Murray	DPaW	Res	Kathy.Murray@DPaW.wa.gov.au
Kelly Waples	DPaW	Res/Man	Kelly.Waples@DPaW.wa.gov.au
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Kevin Bancroft	DPaW	Res	Kevin.Bancroft@DPaW.wa.gov.au
Kim Friedman	DPaW	Res	Kim.Friedman@DPaW.wa.gov.au
Kim Smith	DoF	Res	Kim.smith@fish.wa.gov.au
Kimberley Van Neil	UWA	Res	kimberly.vanniel@uwa.edu.au
Michael Rule	DPaW	Res	Michael.Rule@DPaW.wa.gov.au
Ming Feng	CSIRO	Res	Ming.Feng@csiro.au
Nick Caputi	DoF	Res	Nick.caputi@fish.wa.gov.au
Richard Silberstein	CSIRO	?	Richard.silberstein@csiro.au
Scott Whiting	DPaW	Res	Scott.Whiting@DPaW.wa.gov.au
Steve Newman	DoF	Res	Steve.newman@fish.wa.gov.au
Todd Quartermaine	DPaW	Man	Todd.Quartermaine@DPaW.wa.gov.au

Table A3.2 Assets considered in the survey.

Assets
Finfish:
Coral
Seagrass
Invertebrates
Intertidal
Mangroves
Turtles
Cetaceans
Water Quality
Coastal Biological
Wilderness

A 3.1 Survey Results

Figures A3.1 to A3.4 present the summary statistics for the survey results. The figures show the frequency of response rates against the condition/pressure metrics associated with the coastal and marine park assets. Each of the assets listed in Table A3.2 was assessed for the various condition/pressure metrics used to manage or assess that asset. Where a respondent considered a requirement or potential use for the data to support monitoring the condition/pressure, a count was added to the tally. For example, temperature measurements were deemed to support assets such as seagrass, turtles and water quality (amongst others), so three counts would be added to the temperature tally for these three assets. The following results do not indicate the relative importance of the metric or measurement type to the individual respondents.

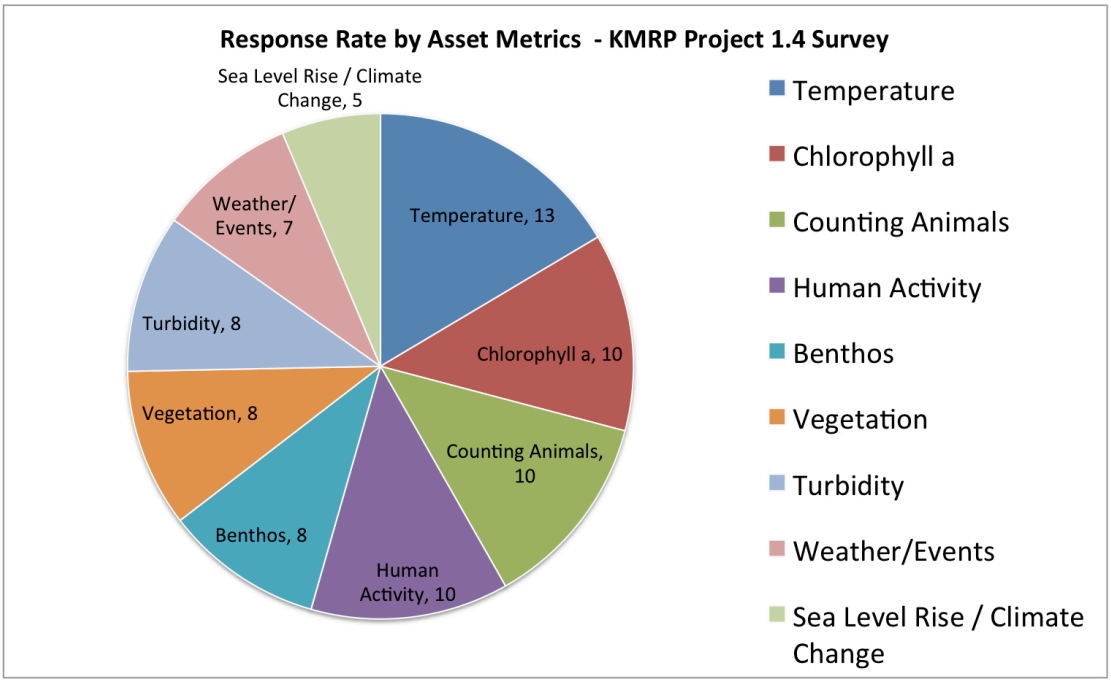

Figure A3.1 Frequency of response by Asset Condition/Pressure metrics.

Figure A.3.1 shows the frequency of response rate for condition/pressure metrics for all assets. Three of these metrics have been separated into sub-classes, for example temperature is separated into sea surface temperature (SST), air temperature, and "other". Data for the three sub-class metrics, Temperature, Human Use, and Counting Animals are shown in Figures A3.2 – A3.4.

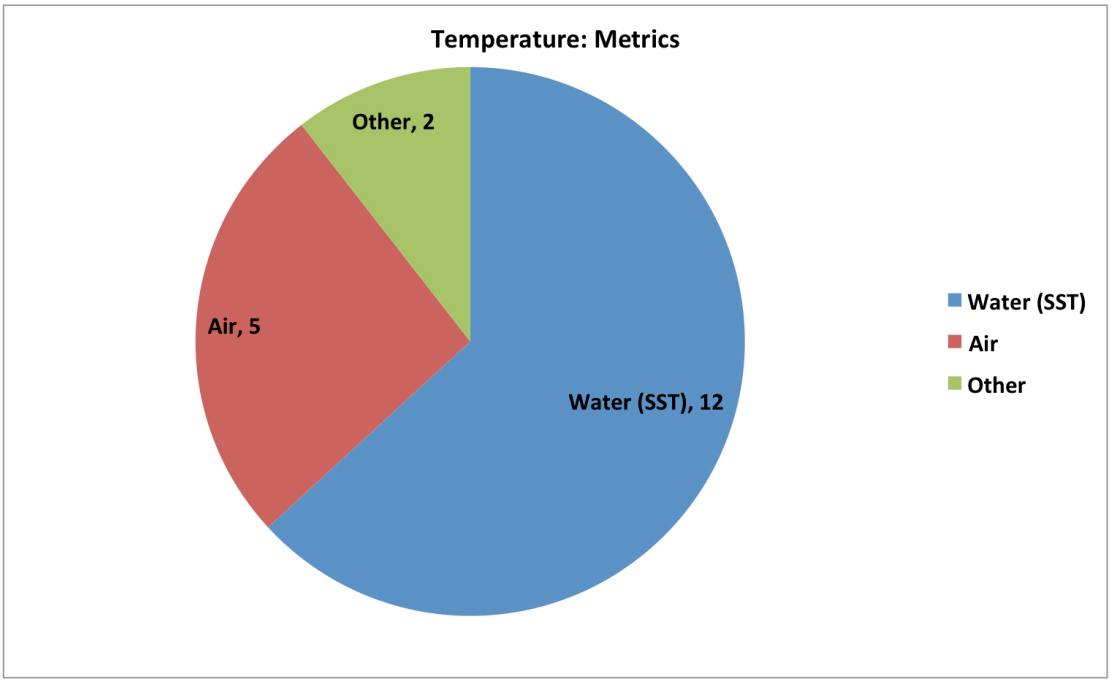

Figure A3.2 Temperature requirements divided into sub-classes.

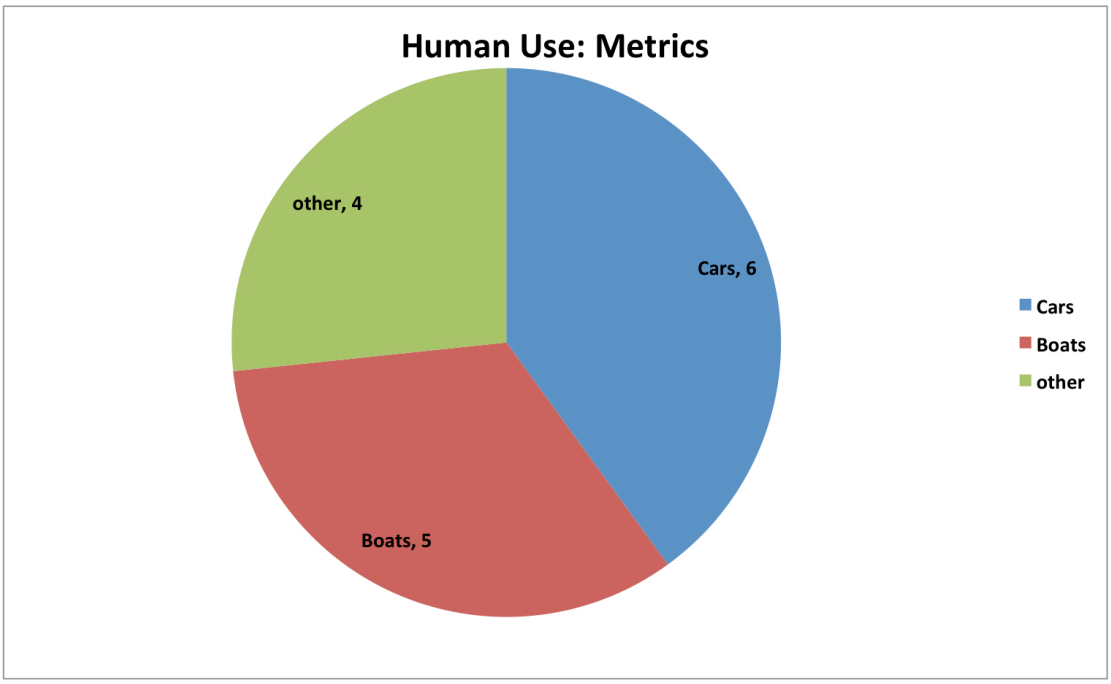

Figure A3.3 Human use measurements by sub-class.

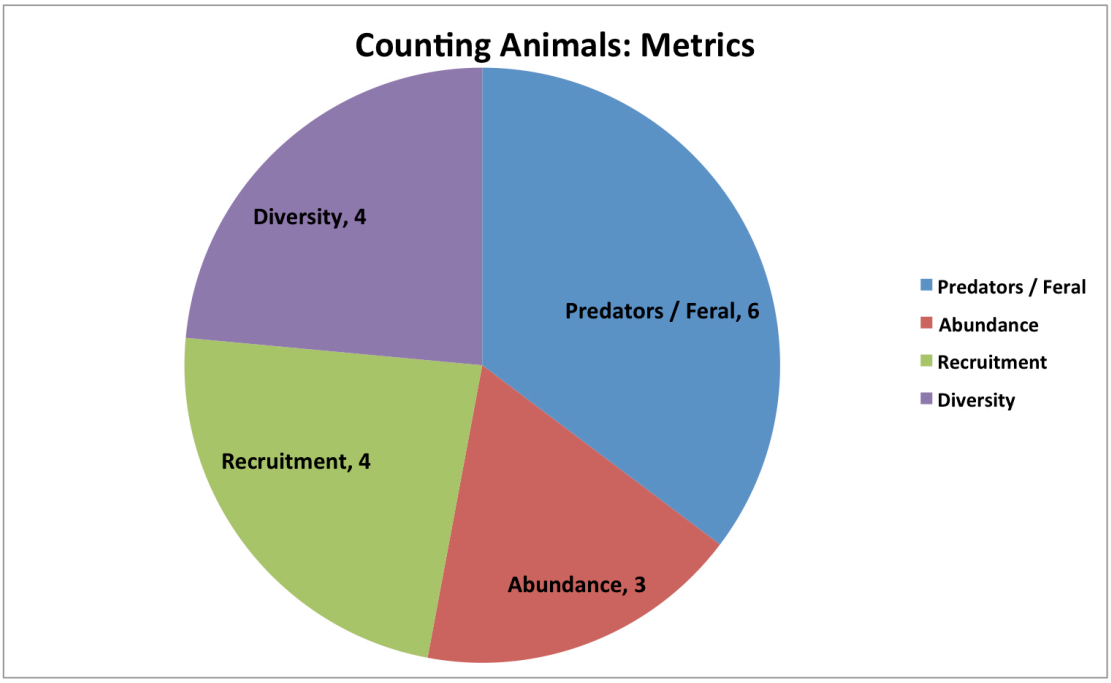

Figure A3.4 Animal monitoring requirements divided into sub-class.

A 3.1.1 Temperature

The charts in Figures A3.1 and A3.2 clearly show that temperature, specifically SST, accumulated the highest frequency of response. Figure A3.2 shows the "breakdown" of temperature responses by sub-class for each asset. For example, where the asset "Coral" required both air temperature and water temperature, this accumulated only one count for the data shown in Figure A3.1, but this is divided into a count for "air" and a count for "water" as displayed in Figure A3.2. If we had included the three sub-classes for temperature in Figure A3.1, the total counts for the three temperature classes would be 19.

Chlorophyll and Turbidity

Figure 1 shows that the metric Chlorophyll accumulated 10 counts. In general the feedback from respondents was that chlorophyll information may be related to productivity and/or water quality. Another metric, "Turbidity", may be related to water column chlorophyll concentration, but may also indicate high levels of suspended sediment. When the interest of the researcher or manager is turbidity this often related to issues of light levels at the benthos (e.g. assets seagrass and coral may be impacted by changing light levels, although this was not always expanded upon by respondents). All respondents indicated chlorophyll information at moderate resolution was the most appropriate (250 m to 1 km).

Human Activity and Counting Animals

Human Activity and Counting Animals may both be divided into sub-classes. These results are shown in Figures A3.3 and A3.4 respectively. If we consider the total responses accumulated across all sub-classes then the total for Human Activity would be 15 and for Counting Animals 17. The modes of collecting data for human activity included such methods as questionnaires/surveys at boat ramps, mounted cameras, and airborne surveys of coastal tracks and associated damage.

Counting Animals included methods (including non-remote sensing methods) such as mounted cameras on beaches, sub-sea baited video, drop camera, diver surveys and tagging. The notion of spatial scale was not explicit, however respondents indicated that most approaches required localized sampling which may then be used to extrapolate to population statistics. The sub-classes for Counting Animals are related to different perspectives of analysing the counting data.

Both Human Activity and Counting Animals tend to utilize localized data capture methods. Current methods appear to be not well established within DPaW.

Coastal vegetation and Benthic Mapping

Coastal vegetation and benthic habitat mapping both accumulated 8 counts, as shown in Figure A3.1. All responses for benthic mapping were either at high spatial resolution (less than 30 m) or *in situ*. Coastal vegetation was also high resolution and *in situ*, with the inclusion of medium (30 m to 250 m) resolution for the Mangroves and Coastal Biological assets. Respondents suggested that the majority of the monitoring involves assessing for loss (or change) of habitat (coastal dune grasses, seaweed beds, corals etc.). Respondents reported some established and emerging methods for using Landsat data (30 m resolution) and higher resolution commercial sensors for monitoring changes in Mangrove extent.

Weather Events, Sea Level Rise and Climate Change

Figure A3.1 shows that Weather Events accumulated 7 counts, however if we divide the metric into impact (storm damage impacting park assets) and typical weather station monitoring (rainfall, air temp, humidity etc.) and related factors such as wave heights and river discharge, then the total counts may be reported as 12. Although the information is not tabulated, respondents indicated that the spatial scales for the broad range of weather events ranged from high resolution to broad scale (low). Weather data are collected via weather stations as well as from the Bureau of Meteorology (based on satellite data and *in situ* etc.).

Sea level rise, linked to effects of climate change, was identified by a few respondents as a metric of interest, but was not necessarily ranked as a metric requiring real-time monitoring. The study of sea level rise and its impact on assets such as Mangroves, Turtles and Coastal Biological, and the prediction of the extent of sea level rise, is an issue to be considered over relatively long time scales (perhaps at least 30 years). Tide gauges collect information on instantaneous water height at specific locations. Long term monitoring coupled with sea level change modelling and knowledge of coastal topography all combine to allow estimates of the impact of sea level rise on assets.

Example Asset Spreadsheet. Condition and pressure metrics for the Coral Communities asset. It lists a number metrics in the first column and has a number of other columns with topics to comment on that metric. The table continues over 6 pages.

Coral Communities

Condition Metrics (followed through time)	RS possibility Y/N	Current tool/s	Effect. (1 - 5)
C: Benthic cover	Y	In-situ and imagery	
C: Spp. composition	N	In-situ and imagery	
C: Diversity	N	In-situ and imagery	
C: Size Frequency	N	In-situ and imagery	
C: Recruitment	N	In-situ and Tiles - Settlement as a surrogate	
Pressure Metrics (followed through time)	RS possibility Y/N	Current tool/s	Effect. (1 - 5)
P: Temp (air and water)	Y	In situ loggers	
		Weather stations	
		SST (NOAA)	
P: Cyclones	Y	Satellite tracking	
P: Sedimentation	Y	In situ sediment traps	
		Sattelite mapping plumes - MODIS	
Light Availability (Turbidity)		In situ loggers	
		Satellite (CHl-a measurements as surrogate)	
P: Predation	Broad scale impacts - Y	In - situ	
		divers	
		visual interp.	
P: Vessel activity	Y	remote cameras	
		patrol observations	
		traffic counters	
		boat ramp surveys	
P: Acidification (long term need)			
Notes:			
This colour denotes information provided by M. Broomhall			

Table A3.3 : Coral communities asset spreadsheet (continued on following pages).

Possible tool or technology	Feasibility	Costs	Rank (1 -5)
Hyperspectral satellite or aerial survey		high	
Possible tool or technology	Feasibility	Costs	Rank (1 -5)
MODIS, AVHRR, MTSAT, Landsat, basically anything that has the 10 – 11, 11 – 12 µm bands	MODIS, AVHRR very feasable, more problematic but feasible with GEO and Landsat	Low	
worldview? Hyperspectral??			

Table A3.3 – Cont.

Availability of Historical data	Rank (1 -5)	Spatial / Temporal issues	Rank (1 -5)
Low		Low / 1 off	
Availability of Historical data	Rank (1 -5)	Spatial / Temporal issues	Rank (1 -5)
Back to 1981 (not sure iff this included AUS)		Monthly, weekly and daily product available, on 1 and 1/4 degree grid (100 - 25 km res)	
Landsat back to lat 70s, AVHRR mid 80s, GEO back to late 70s, MODIS 1999 onwards		High coverage, low to medium spatial resolution, daily coverage, long time-series possible	

Table A3.3 – Cont.

Problems with access to RS data or data products	Rank (1 -5)	Problems with interpretation	Rank (1 -5)
shallow water only		Cannot always differentiate between macro algae; turf reef and coral reef	
Cannot differentiate taxonomy			
Cannot differentiate taxonomy			
Cannot differentiate individual colonies			
resolution			
Problems with access to RS data or data products	Rank (1 -5)	Problems with interpretation	Rank (1 -5)
Have immediate access to MODIS archive, AVHRR, GEO and Landsat are free but would need to be obtained		Product is uncertain near the land/water boundary, Skin temp only not at depth	

Table A3.3 – Cont.

Future research needed	Rank (1 -5)	Time required for future research to apply this solution	Rank (1 -5)	Cost for future research to apply this solution	Rank (1 -5)
Camparison - Ground truthing - New Sat technology		high			
Future research needed	Rank (1 -5)	Time required for future research to apply this solution	Rank (1 -5)	Cost for future research to apply this solution	Rank (1 -5)
Mature product					
Mature product					

Table A3.3 – Cont.

MPA manager comments	Other Provider comments	Score?
MPA manager comments	Other Provider comments	Score?

Table A3.3 – end.