National Environmental Science Programme

Earth Observation for monitoring of Australian Marine Parks and other off-shore Marine Protected Areas

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Project D2: Standard Operating Procedures for Survey Design, Condition Assessment and Trend Detection

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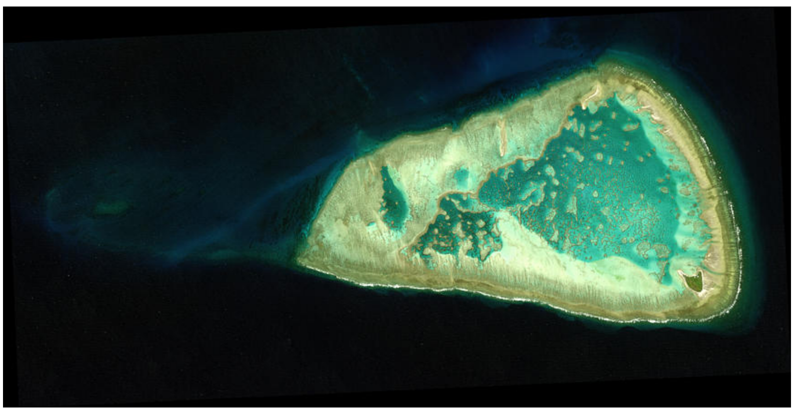

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EXECUTIVE SUMMARY

Off-shore and coastal Marine Protected Areas (MPAs) are a recognised conservation tool to assist in the management of multiple pressures, including human activities and global climate change. Australia's network of Marine Parks was designed in order to protect the biological diversity in Australian waters on a bioregional, ecosystem, habitat, community and species level. The management plans introduced in 2018 for these marine parks include a number of programs and actions that require monitoring and decision making capabilities across Australia's vast marine estate, however one of the biggest challenges is the implementation of monitoring technologies and acquisition of data across such a large region. These management plans highlight the potential for new technologies to help underpin these capabilities, and in this report we discuss the potential and nature of the role Earth Observation (EO) can play in MPA monitoring.

EO satellites provide a wide array of data types, services and products that have a well recognised potential to feed into the monitoring of environmental variables in a systematic and repeatable manner (see Tables 2 & 5). However, to date there has been limited uptake of EO products for systematic Marine Park monitoring and reporting in Australia, despite there being a long history of marine scientific product development both globally and within Australia, from a range of EO data sources. In this report we begin by introducing EO data and science products in the context of marine monitoring, and give an overview of data availability in Australia (Section 1).

In Section 2, we provide a more detailed overview of core EO scientific products in the marine space, with a focus on Australian applications and programs. Covering ocean colour, sea surface temperature and coastal water applications, a number of case studies relevant to MPA monitoring within Australia are used to demonstrate the potential of EO, whilst also providing an opportunity to examine some of the barriers and challenges to adoption by the broader marine parks community.

Section 3 focuses on human induced pressures on the marine environment and uses a range of case studies to illustrate the role EO scientific products can play in more effective mapping, monitoring and assessment of the impacts of these pressures. In Section 4 we highlight some of the future trends and developments in marine EO data, products and infrastructure, and discuss the potential impacts and opportunities from a MPA monitoring perspective.

In a summary discussion, we revisit the challenges that exist for the adoption and uptake of EO products for MPA monitoring. We focus on the importance and benefit of increased communication and engagement between Marine Park managers and EO technical practitioners, particularly in the earlier stages of the products development cycle. Attention is drawn to one of the key themes of this report, that EO data and products have the highest potential impact in Marine Park monitoring when used as a complimentary data source, within a collaborative and multi-disciplinary environment.

1. INTRODUCTION

Stephen Sagar (GA) and Inke Falkner (GA)

1.1 Marine Protected Areas

Marine protected areas (MPAs) are an important conservation tool in the protection of marine biodiversity (Worm et al., 2009). Historically MPAs have been established in coastal and shallow waters to manage the multiple pressures arising from competing human activities and their design has been based on species' distributions, benthic habitats and geomorphological features.

In recent years, however, in response to dwindling fish stocks, global climate change and the impacts of other human activities on biodiversity, large off-shore Marine Protected Areas (MPAs) have been established worldwide. Many of these vast marine reserves have been created to protect high-seas ecosystems including highly mobile marine species. However, methodologies and technologies to collect the ecological data to monitor and assess the effectiveness of these large MPAs have not necessarily kept pace with their establishment (Pala, 2013; but see Kaplan et al., 2013).

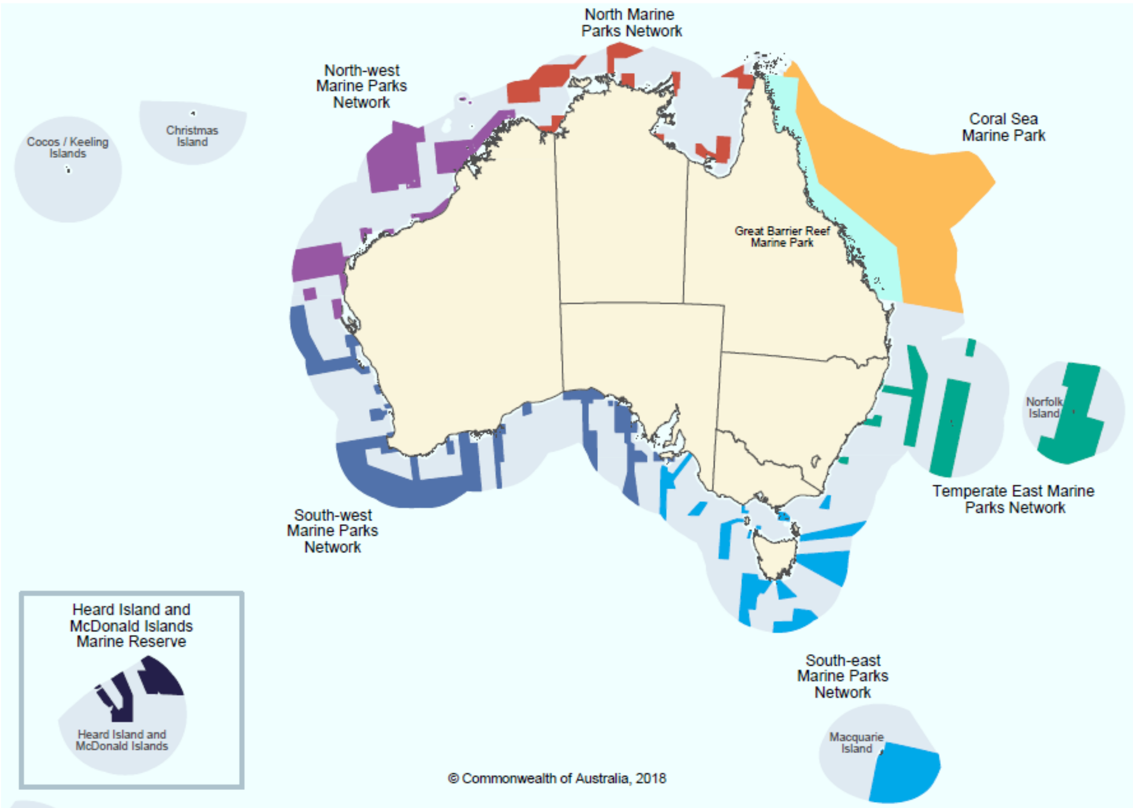


Figure 1 – Australia's Network of Marine Parks

Australia's national network of Australian Marine Parks (Figure 1) was designed following the principles of comprehensiveness, adequacy and representativeness in order to protect the biological diversity in Australian waters on a bioregional, ecosystem, habitat, community and species level. The network of MPAs was informed by the Key Ecological Features identified from the Integrated Marine and Coastal Regionalisation of Australia (IMCRA 4.0). IMCRA 4.0 comprised of 41 'bioregions' representing large areas of ocean with broadly similar characteristics. These bioregions were developed using scientific information from detailed surveys, which is only available for a very limited area of Commonwealth waters, benthic surrogate information such as bathymetry and geomorphology, and sponge and fish distributions

In 2018, management plans for five of the six Australian Marine Parks networks were introduced by Parks Australia, with the exception of the South-East Marine Park Network for which management plans were introduced in 2013 (Department of the Environment and Energy). These plans detail the vision for management of marine parks within Australia, zoning categories and rules for activities, and management programs and actions available to manage each individual park. These management programs include a marine science program, park protection and management program and a compliance program, as follows:

The Marine Science Program aims to increase our understanding of marine park values, pressures and the effectiveness of marine park management in protecting park values and goals listed under the Park protection and management program. Specific actions under this program include:

- Establishing ecological baselines to support evidence-based decision-making and adaptive management;
- Establishing an authorisation system for scientific research and monitoring by third parties, and encouraging data to be made publicly available through the appropriate information portals such as the Australian Ocean Data Network;
- Collaborating with the science community and prioritising and encouraging research and monitoring of park values, pressures and management effectiveness; and
- Increasing the use of innovative and effective technologies and systems including sensor technologies;

The Park Protection and Management Program includes preventative and restorative actions that aim to minimise the impact of pressures as far as possible. Specific actions include:

- Application of risk-based assessments;
- Development of a critical incident strategy to respond to environmental incidents and accidents;
- Support the removal of marine debris and ghost nets.

The Compliance Program, which includes actions that support appropriate compliance by marine park users including targeted enforcement. Specific actions include:

- Investigating the use of new technologies and warning systems to assist in the detection of potential illegal activities

Within these programs there is great potential to integrate Earth Observation (EO) derived products and enable the improved delivery of many of the specific action points.

1.2 Earth Observation in MPA monitoring

Earth observation from satellites has revolutionized our view of the oceans and offers vast potential for marine monitoring. With advances in spatial, temporal and spectral resolution satellite remote sensing is now used in coastal and estuarine habitat mapping and the monitoring of ecosystem services in order to inform marine spatial planning and integrated management (Kachelriess et al., 2014, de Araujo Barbosa et al., 2015, Hedley et al., 2016 and Ouellette and Getinet, 2016; Stachelek et al., 2018). Satellite remote sensing data has also been successfully integrated into coastal ecosystem risk assessments (reviewed in Murray et al., 2018).

Monitoring environmental change and assessing biodiversity effectively in large and remote off-shore MPAs using satellite remote sensing has proven challenging, and it is important to recognize that remote sensing only provides information about the upper layer of the ocean. However, the wider international marine science community, and ocean observing community in particular, have long recognised the potential for earth observation to play a larger role in a range of marine monitoring applications. In a recent paper by Groom et al., (2019), they reflect on the community white papers presented at the OceanObs'09: Sustained Ocean Observations and Information for Society, noting clear needs and potential for operational and sustainable earth observation systems to address issues such as pollution, eutrophication, climate and carbon products, marine ecosystem health, fisheries and aquaculture.

Groom et al., (2019) also note that earth observation, and ocean colour in particular, plays an important cross-cutting role in the Essential Ocean Variables (EOVs) developed by the Global Ocean Observing System (GCOS, 2016; GEO BON, 2016), and more recently by Miloslavich et al., (2018). To complement these EOVs, Essential Biodiversity Variables (EBVs) to standardise observations of biodiversity and climate change that will be applicable in pelagic environments have been developed by the GEO Biodiversity Observation Network (GEO BON) (Muller-Karger et al., 2018). These variables include measurements of phytoplankton community composition, distribution and abundance and ecosystem function variables such as net primary production, ecosystem extent and substrate classification (GEO BON, 2016). These globally established variables have the potential to be adopted into established marine park monitoring programs, underpinned by earth observation data.

Beyond direct monitoring of ecological and biological variables, earth observation has the potential to monitor a range of event-based and potentially threatening anthropogenic influences such as oil spills, illegal fishing and marine debris (Kachelriess et al., 2014). Whilst validation of these detections is challenging, this capability provided by EO can act as a tool to more effectively and efficiently deploy resources to manage these issues.

Whilst timely monitoring is without doubt an important aspect of MPA management, the length of archives provided by some EO sensors also enables the establishment of historical baselines. A continuous spatial and temporal record provided by EO can be used to supplement in-situ records and add both finer and broader scale context for a range of environmental variables. This kind of historical record can also be used to shed light on broader scale drivers for observed local events. For example, EO can enable habitat or ecosystem health changes observed in the field, such as coral bleaching or seagrass extent, to be linked to drivers at a broader scale such as increased or varied patterns of sea surface temperature (SST).

Satellite remote sensing not only provides us with a synoptic view of dynamic open water and coastal ecosystems; it also has the potential to give us repeatable, standardized and verifiable information to monitor off-shore protected areas on global and regional scales.

1.2.1 Challenges to Adoption

One of the first barriers to adopting remote sensing products for MPA monitoring that is often discussed is the cost of data (Kachelriess et al., 2014). Although the cost of data from many high resolution commercial sensors can be prohibitive for monitoring purposes, the free and open data policies offered by key space agencies is driving increased uptake for remote sensing across all environmental applications (Paganini et al., 2016). The trade-off between spatial resolution and cost of data still remains (discussed more thoroughly in section 2.3), although this is closing quickly as technology advances.

Another important issue to consider is the translation and alignment of EO derived products to the reporting metrics required by agencies and departments which monitor and report on MPAs. Ensuring that the variables and metrics delivered by EO products do not require conversion, refactoring or interpretation by a technical user is an important consideration when there is an expectation that policy and reporting personnel will integrate these data into a reporting workflow. Likewise, data access, formats and analytical summaries must be carefully considered to address the needs of potentially non-scientific or technical users.

There is also a need for the EO community to actively incorporate user feedback and needs into their products, as well as provide functional advice as to the role different products may play in a full integrated observing system. An increased focus on delivering associated uncertainty and confidence indicators with EO products is one example being driven by user requirements (Groom et al., 2019). By increasing user understanding of how EO products play a role along with other measurements and methods (in-situ networks, modelling etc), uptake is also likely to increase. In this way, EO products will be seen less as a stand-alone solution, and more as a complementary data source to enhance both spatial and temporal analysis, when suitably calibrated and/or validated with in-situ measurements.

1.2.2 Open Access Data within Australia

Satellite missions which provide open access earth observation data for Australia are managed through international agencies such as NASA, NOAA and the USGS in the United States, and ESA and EUMETSAT in Europe. These agencies provide a wide range of portal and access mechanisms for their EO data, at all stages of the processing chain, from radiance observed at the satellite through to gridded interpreted products such as water constituent concentrations and other geophysical variables (see also Tables 2 and 5).

Within Australia there are a number of initiatives that recognise the need to tailor the processing of these data sources for regional environmental conditions and increase their utility for Australian applications.

From a marine perspective, the most significant of these is the satellite remote sensing facility within the Integrated Marine Observing System (IMOS). This BoM and CSIRO collaboration provides ocean colour and sea-surface temperature products via the Australian Ocean Data Network (AODN). https://portal.aodn.org.au/ (For further details see Sections 2.1.3 & 2.2.3)

Copernicus Australasia is a regional hub as part of a collaboration between the Australian Government and the European Commission, providing open access to data from Europe's Sentinel satellite missions for the South-East Asia and South Pacific region. This data can be accessed via the NCI and through the Sentinel Australasia Regional Access (SARA) interface. https://copernicus.nci.org.au/sara.client/#/home

Digital Earth Australia (DEA) is a Commonwealth Government program which provides an analytical platform for earth observation data such as Landsat and Sentinel-2, through a combination of webservices, high performance computing access platforms and visualisation portals (see Section 4.1.3)

1.3 Objectives and Scope

This report aims to provide an introduction to earth observation (EO) concepts in the context of their application to marine park monitoring and reporting.

In Section 2 we provide an overview of some of the fundamentals of EO methods in marine and coastal environments. Alongside a description of the basic science, sensors and algorithms used, we illustrate some case study examples of how these types of data can be used from a marine park management perspective.

In Section 3 we highlight a range of case study examples demonstrating the potential of EO to detect and monitor human induced pressures in marine environments. Many of these examples draw on the EO concepts in Section 2, and demonstrate how EO datasets can have multiple uses, often as a highly complementary dataset.

Section 4 discusses future trends in EO data, sensors and applications and their relevance to marine applications.

The applications discussed in this report focus primarily on marine and coastal aquatic applications of earth observation. There can inevitably be a component of terrestrial analysis required when holistically monitoring a marine park (e.g. vegetation cover on coral cays), however these applications are not within the scope of this report.

2. FUNDAMENTAL EARTH OBSERVATION FOR MPA MONITORING

2.1 Ocean Colour

Arnold Dekker (SatDek Pty Ltd)

2.1.1 General Background

The colour of the ocean is determined by the interactions of incident light from the sun and sky (blue sky, clouds etc.) with pure seawater and the dissolved and/or particulate matter in the water. Blue ocean water contains mainly small amounts of algae and its breakdown products, greener waters have higher algal concentrations and often higher dissolved organic matter concentrations, brown waters often have high suspended sediment concentrations. Satellite earth observation of ocean colour measures the reflectance from the coastal or ocean water in space. By analysing the spectral reflectance measured by the satellite sensor, and after removing the atmospheric light interactions, the optically active constituents can be retrieved (see Table 1).

Modified after a review of ocean colour by Groom et al., (2019), we summarise the following application fields where ocean colour earth observation can play a critical role, acknowledging that these span the continuum from research through to operational in a EO context :

- The global carbon cycle and its fluctuations at many time scales;
- Ocean acidification;
- Marine biodiversity and function;
- Validation and improvement of Earth System and ocean biogeochemical models;
- Data assimilation to improve model performance;
- Data for assessing impact and adaptation of marine ecosystem to climate change;
- Bio-feedback mechanisms, understanding Earth System;
- Flow of material through the marine food webs, implications for marine resources;
- Marine pollution;
- Eutrophication
- Nutrients and sediments from terrestrial sources

The sensors on board the satellites that measure coastal and ocean colour have many more spectral bands then the three bands the human eye can see (blue green, green and yellow-red) and thus it would be more correct to call this “coastal and ocean spectral sensing”. The current satellites specifically designed for coastal and ocean water earth observation have between 7 and 22 spectral bands covering the visible and nearby infrared (NIR) wavelengths. Near future hyperspectral ocean colour satellites will have imaging spectrometry capability across 340 to 890 nm in the ultraviolet (UV) to near infrared, equating to 110 spectral bands. As the number of spectral bands increases the detection and identification of optically active constituents increases substantially e.g., discriminating diatoms, coccolithopores, green algae and cyanobacteria etc., or discriminating coloured dissolved organic matter whether it comes from a terrestrial source or from an ocean source. It will also be increasingly possible to determine particle size distributions. As the diagnostic power of Ocean Colour increases with the sophistication of the sensors less in situ measurements are required to validate the products.

Properties associated with phytoplankton =free floating algae in the water column or floating at or near the surface:

- Chlorophyll-a concentration
- Cyanobacterial pigments (mainly cyanophycocyanin and cyanophycoerythrin)
- Other algal pigments (by HPLC)
- Algal species
- Phytoplankton functional types
- Algal blooms and potentially harmful algal blooms

Properties associated with aquatic plants in the water column or floating at or near the surface (see also Section 2.3.1):

- Macro-algae (such as kelp)
- Water plants (such as seagrasses)

Properties associated with dissolved organic coloured material:

- Coloured dissolved organic matter (CDOM) – may be of terrestrial or oceanic origin

Properties associated with inanimate material suspended in the water column:

- Total suspended sediment composed of:
  - Inorganic suspended sediment fraction
  - Organic suspended sediment fraction
- Size distributions of non-algal particles

Optical properties of the water column that result from any combination of the above optically active constituents:

- Secchi Disk transparency
- Turbidity
- Vertical attenuation of depth

Table 1 - Optically active constituents for which products can be produced from ocean colour earth observation data. Note: These products range in maturity from research through to operational applications.

The physics of how light interact with the atmosphere, the air-water interface and the water column is required to understand how the algorithms (the mathematical or statistical methods used to translate a measured light signal measured at the satellite, reflected from the coastal or ocean water) work. There are many textbooks on this, here we will present only the guiding principles. Sun light and skylight entering a coastal or ocean waterbody are modified in the water column causing the colour of the waterbody to be different from the colour of the incoming light (which will be a mixture of white from the sun or blue from a clear blue sky). There are two main processes that cause this change in colour: the absorption and scattering of light by the substances in the water. In fact, it is the backscattered light that is registered at the satellite sensor as radiance, which can be converted into reflectance. One additional process is to measure the chlorophyll-a fluorescence of the phytoplankton in the water column from space. Fluorescence is the process whereby phytoplankton absorb light (making use of their photosynthetic light harvesting pigments), use most of it for photosynthesis but emit some photons at a wavelength of 683 nm (deep red). This fluorescence can be a measure of the concentration and health of the phytoplankton.

SENSORS

The contiguous satellite observed ocean-colour record reached 22 years in 2019; however, it is comprised of a number of one-off satellite missions such that creating a consistent time-series of ocean-colour data requires merging of the individual sensors (including MERIS, Aqua-MODIS, SeaWiFS, VIIRS, and OLCI) with differing sensor characteristics, without introducing artefacts. By contrast, the next decade will see consistent observations from operational ocean colour series with sensors of similar design (VIIRS and Sentinel-3 OLCI) and with a replacement strategy. By 2029 the 30 year record will start to be of sufficient duration to reliably discriminate climate change impacts from natural variability, at least in some regions (Groom et al., 2019).

The four key measurement characteristics of ocean and coastal spectral Earth Observation sensors are the spatial resolution (or pixel size), the spectral resolution (the number of spectral bands and their location in the spectrum with respect to the optically active constituents to be measured e.g. phytoplankton pigment absorption), the radiometric resolution (how many levels of upwelling radiance or reflectance can be distinguished) and the temporal resolution (how often and at what time of day the satellite observes the same area).

Table 2 presents a summary of all satellite sensors relevant to oceanic ecosystems. For larger coastal and ocean waters, ocean colour sensors are most relevant as well as the geostationary sensors. The coastal ocean sensors are all in a Low Earth Orbit (LEO) typically at 600 to 800 km altitude and circle the globe in about 100 minutes. As the world rotates the satellite sensors image an adjacent strip of land and ocean every 100 minutes- thus building up a global image database. The overpass time is usually between 09:30 and 14:30 local solar time.

The geostationary sensors are positioned at a fixed location above the equator at 30,000 km altitude and can image a fixed location every 10 minutes. Except for the South Korean GOCI-I and II geostationary sensors (permanently positioned over Indonesia but looking at the Korean-Japanese ocean waters) no geostationary sensors are available above Australia designed for ocean colour. A new generation of meteorological satellites (Himawari-8 and 9) are located above the equator to the North of Australia and do provide 4 spectral bands (blue, green, red, NIR) of relevance to ocean studies.

The most relevant ocean colour sensors for Australian marine parks are MODIS (two satellites MODIS-Terra and MODIS Aqua), the JPSS series of satellites (with the VIIRS sensor on board) and the Sentinel-3 series of satellites with the OLCI sensor. Other ocean colour sensors and satellites do exist but require more specialist intervention to be made useful for operational use as they are one off instruments. Both ESA and NASA are providing global merged products from all these sensors to allow for more climate change type studies.

Improvements in sensor engineering of ocean colour sensors has enabled the spatial resolution to increase from 1 km to 0.3 km pixels. The frequency of image acquisition stays approximately the same with one to two images for the same area every day. The spectral resolution however has deteriorated for the US sensors of MODIS (9 bands) to VIIRS on JPSS (7 bands) whereas for the European sensors the spectral bands have increased from

15 for MERIS (2003-2012) to 21 for Sentinel-3 from 2016 onwards. This increase in spatial and spectral resolution enables more accurate discrimination of the optically active substances in the water column. The radiometric resolution has remained at a similar level.

ALGORITHMS

Ocean colour Earth observation algorithms translate the satellite measured reflectance from a water body to water quality variables listed above. There are several approaches to algorithms, after CEOS, (2018). The algorithms for translating the measured spectral reflectance from a water body to water-quality variables range from: (i) empirical approaches (See reviews by Matthews, 2011 and Tyler et al., 2016); (ii) semi-empirical approaches (Gons, 1999; Härmä et al., 2001)); (iii) physics-based, semi-analytical spectral inversion methods (Lee et al., 1998; Brando et al., 2012; Odermatt et al., 2012) to (iv) Artificial Neural Network and Machine Learning Methods and (v) Object Based Image Analysis methods.

The empirical and semi-empirical methods need a lot of in situ data for the ocean colour products to be valid. The physics-based methods need the least in situ data for validation. The ANN and ML methods need a lot of either simulated data or in situ data for training purposes.

The various approaches to algorithms are outlined below and compared in terms of their need for field measurements, as well as their reliability, accuracy, maturity, and complexity.

Empirical approaches statistically relate field observations of the optical water-quality or benthic variables to radiance or reflectance values measured by a satellite. These methods are less reliable when undertaking retrospective monitoring, especially when water-quality or benthic characteristics may change and end up outside the range of those upon which the empirical relationship is based.

Semi-empirical algorithms improve over pure empirical approaches by choosing the most appropriate single or spectral band combination to estimate the water column or benthic constituent. Although preferable over empirical algorithms they still require new, semi-empirical algorithms when switching between satellite sensors or when measuring new water bodies.

Semi-analytical inversion algorithms are built around knowledge of the underlying physics of light transfer in waters and use the inversion of predictions of light reflecting from a water body, generated by forward radiative transfer models, to simultaneously estimate key water-quality and benthic constituents. Such approaches show improved accuracy for estimating water-column composition (Dekker et al., 2002), and are capable of assessing the error in the estimation of water-quality constituents, are repeatable over time and space, are transferable to new water bodies and other sensors, and can be retrospectively applied to image archives (Odermatt et al., 2012).

Artificial intelligence (AI) methods such as an Artificial Neural Network (ANN) and machine learning (ML) methods are becoming more powerful as computing power increases. ANN and ML methods can be trained using a radiative transfer model or using a bio-optical semi-analytical model or they can be trained using large amounts of in situ data.

The most likely globally valid methods for use in areas where there may be little or no in situ data for verification or for dealing with the vast range of possible types of waters are the methods that are based on understanding and simulating the physics of light interaction in the atmosphere, the air-water interface, the water column and the benthos.

Sensor Type	Platform	Sensor	Spatial Resolution = Pixel Size	Spectral Bands (400 - 1000nm)	Revisit Frequency (at equator)	Launch	Water Quality Variables					
							Chl	CYP	TSM	CDOM	Kd	Turb / SD
Sun - Syn	Terra/Aqua	MODIS A&T	1km	9	daily	1999/ 2000	2	3	1	1	1	1
	Oceansat 2	OCM-2	300m	8	2-3 days	2009	1	1	1	1	1	1
	Suomi/NOAA-20	VIIRS	750m	7	daily	2011/2017	2	3	1	1	1	1
	Sentinel 3 A/B	OLCI	300m	21	daily (with 2 satellites)	2016/2018	1	1	1	1	1	1
	GCOM-2	SGLI	250m	9	2-4 days	2017	2	4	1	1	1	1
Geo	KOMPSAT	GOCI	500m	8	Half hourly	2010	1	3	1	2	1	1
	Himawari 8&9	AHI	500m-2km	4	10 minutes	2014	3	4	1	3	2	1

Table 2 - Current relevant ocean colour earth observation platforms and sensors modified from Groom et al. (2019) and CEOS (2018). 1 – Highly Suited, 2 – Suitable, 3 – Potential, 4 – Not suitable

2.1.2 Ocean Colour for the management and monitoring of MPAs

Here we discuss potential applications of Ocean Colour EO products introduced in the previous section, for management and monitoring of Australian Marine Parks and their surrounding waters. It is necessary to emphasise the word ”potential” as many of these methods have been developed in other parts of the world, but not yet tuned to, or validated for, the Australian ecosystems. To operationalise these methods, it is necessary for the MPA managers to clarify their requirements. This section intends to inform MPA managers in Australia what can be made operational here as it has already been proven to be feasible or operational in other parts of the worlds coastal and ocean waters. If we put his into the definitions of the Framework for Ocean Observing many of the products are in pilot phase for Australia. Australian institutes such CSIRO, Geoscience Australia and academia have the know how to operationalise these products but will not do so without clear end-user pull.

It is useful to discriminate two types of coastal to ocean water here: 1) coastal waters that are under influence from terrestrial runoff as well as from resuspension of bottom materials due to tides and waves and 2) deep pelagic waters where terrestrial influences are negligible on the water properties.

For example, extensive nearshore areas of the Great Barrier Reef (GBR) can be influenced by river plumes from the catchment especially during monsoonal rain events. In addition, many parts of the GBR are shallow and tidal currents can resuspend bottom sediments. However, MPA’s such as the Coral Sea or on the NW Shelf are so far from land that they are mainly subject to ocean water and its variability. In this section we discuss deep pelagic water applications, with complex coastal waters discussed in section 2.3.2

GENERAL

A review paper on the application of ocean colour remote sensing for marine protected area management is presented by Kachelriess et al., (2014). Primary productivity, SST, currents and oceanic front patterns are all important parameters structuring the spatiotemporal distribution of marine biodiversity that can be detected by satellites (Hardman-Mountford et al., 2008) and can be used for pelagic habitat classification (Gregr et al., 2012).

Other aspects of primary productivity (which can inferred from EO products) are via indirect trophic effects on species (Fenberg et al., 2012); and the distribution of highly migratory marine species (e.g., blue shark (Queiroz et al., 2012); bluefin tuna (Druon, 2010); whale sharks (Sequeira et al., 2012); representativeness (Fraschetti et al., 2008); capacity for self-recruitment/larvae retention (Bell, 2012) to identify biological hotspots for cetaceans; and seabirds (Petersen et al., 2008). Areas of high primary productivity have also been shown to be highly correlated with benthic community patterns (e.g., Patagonian scallop; Bogazzi et al., 2005).

A possible application for MPA monitoring is detection of organic particulate matter (CDOM) on coral reefs as an indicator of algae being stripped out of the water by filter feeders on a coral reef ecosystem (Dekker et al., 2012). Sensors such as MODIS, VIIRS and Sentinel-3 have the sensitivity to detect CDOM concentrations, enabling marine scientists to further assess such potential biogeochemical transformation of a reef system.

Hobday (2001) used Ocean Colour and SST to assess physical patterns of Australia's MPA's to assess temporal and spatial shifts in surface environments. They explored the potential for using satellite data to rapidly assess the historical environmental state of Commonwealth MPAs. Sea surface temperature (SST) and sea surface colour (SSC) data were extracted from satellite images. A description of the range and mean conditions was provided. Climatologies generated from these data described the seasonal signal for the surface environment. Univariate habitat definitions for the surface waters were developed using SST and SSC measures, and the temporal and spatial description of these habitats presented. The adequateness and representativeness of the MPAs was evaluated by estimating the fraction of the similar surrounding habitat that is contained within each MPA. Collectively these data potentially provided a baseline for monitoring the pelagic environments of the MPAs and indicated additional regions around Australia without protected surface habitats.

PHYTOPLANKTON, PFT'S, PIGMENTS AND ALGAL BLOOMS

Information on phytoplankton diversity (Bracher et al., 2017), as well as phytoplankton functional types (IOCCG, 2014; Mouw et al., 2019) can be obtained from satellite ocean colour. With increasing spectral resolution available from satellites such as from Sentinel-3 and the near future NASA-PACE mission (see Section 4.1.1) it will become increasingly possible to identify phytoplankton types, species and functional types, and progressively move from research through to monitoring application. Thus, as climate change influences ocean nutrients, acidity and algal blooms, ocean colour may have the potential to detect shifts in algal concentrations and species composition.

Algal blooms are naturally occurring ecological responses to changes in light availability, temperature, zooplankton grazing and nutrients. Algal blooms are also transient phenomena that occur at different scales of time and intensity depending on the latitude, the distance from shore and the season. In the Australian State of the Environment Report 2011 Blondeau-Patissier et al., (2012) (Figure 2) analysed time series of Earth observation data for detecting the dynamics of algal blooms around Australia. Monitoring algal bloom events within a specific location over a long period of time (i.e., several years) has the potential to allow derivation of an ecosystem baseline. This baseline could be used to detect and anticipate changes in the system. A specific earth observation=n based study on the GBR focused on Trichodesmium (Blondeau-Patissier et al., 2018) (Figure 2). The Cyanobacterium Trichodesmium sp. is a marine diazotroph phytoplankton found in all tropical and subtropical oceans. Trichodesmium may form extensive algal blooms over hundreds of kilometres and likely plays key roles in the ecosystem because of its ability to fix atmospheric nitrogen. Trichodesmium colonies also contribute to the phosphorus budget by the uptake of phosphorus for growth, in addition to providing substrate and shelter to various organisms ranging from bacteria to crustacean larvae. As temperature and nutrients are key conditions for Trichodesmium, climate change will change the nature and extent of these blooms for MPAs.

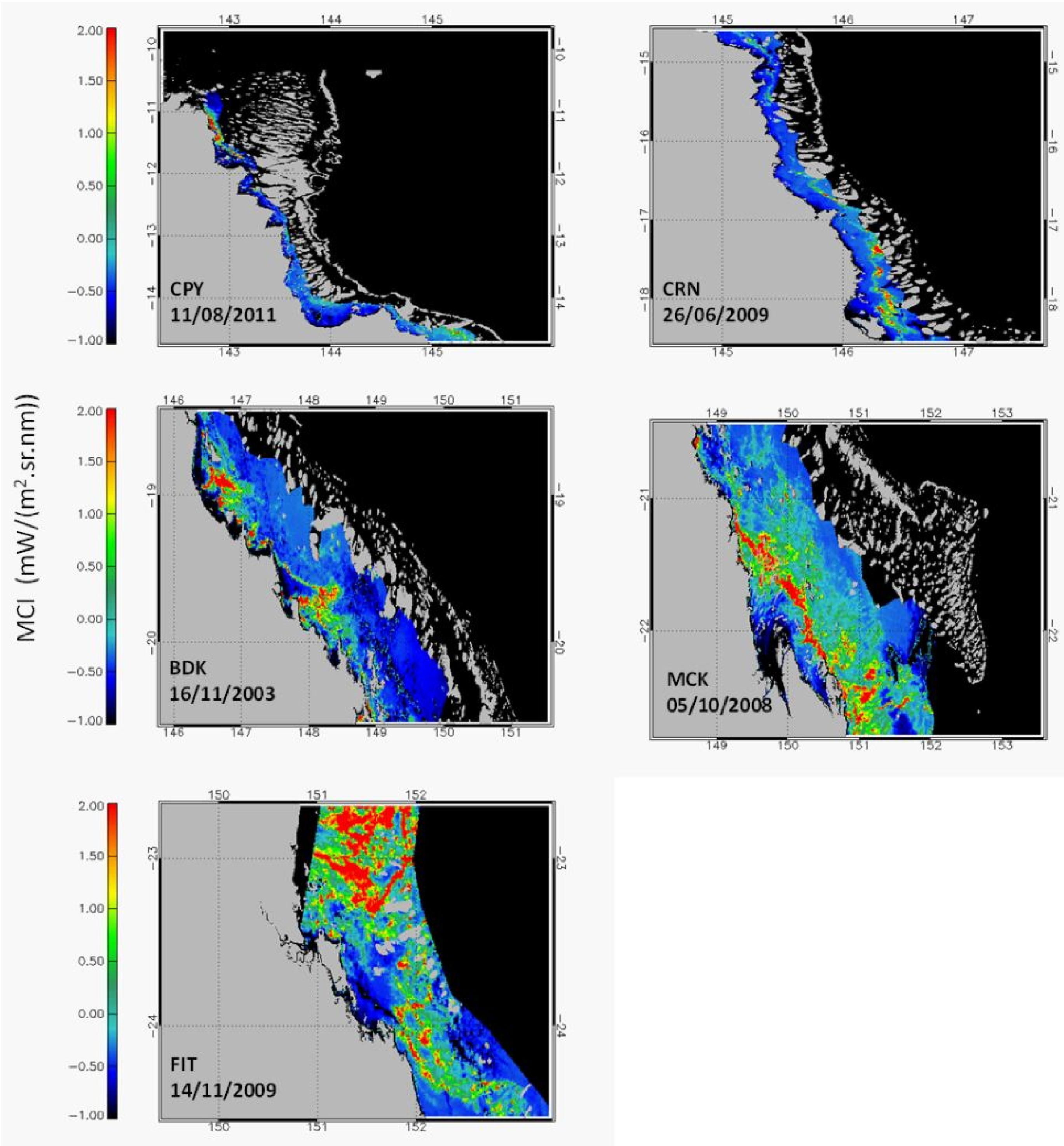


Figure 2 - Largest surface bloom events based on the Maximum Chlorophyll Index (MCI), likely of Trichodesmium spp., captured by Envisat MERIS between 2002 and 2012 in the Great Barrier Reef (Blondeau-Patissier et al., 2018). From top left to bottom left: Cape York region; Cairns; Burdekin ; Mackay; Fitzroy. In situ validation data was mainly derived from the AIMS Long Term Monitoring Program.

2.1.3 Ocean Colour Data Sources

Earth observation data have different levels of pre-processing and processing applied to them. Data are provided at Level-1: raw or calibrated and geolocated observations at native resolution; Level-2: derived geophysical variables at native resolution; and Level-3: derived geophysical variables that have been aggregated/projected onto a well-defined spatial grid over a given time period, including daily, weekly, monthly, seasonal and annual composites.

Note of warning to end-users: most of the data products from the international ocean colour sensors and providers are mainly validated for use in the Northern hemisphere and are biased towards the USA East and West coastal-ocean waters and European Waters. Stated levels of accuracy for these data should not be assumed to apply to Australian waters. Independent validation is recommended, in particular in coastal waters (including the GBR lagoon waters), such as presented in Schroeder et al., (2017).

Data provided in Australia:

One of the primary sources of ocean colour data in Australia is the Australian Ocean Data Network (AODN) managed as part of Integrated Marine Observing System (IMOS) (https://portal.aodn.org.au/). This website is the entry into the IMOS Ocean Colour website with a lot of relevant information for Australian users: http://imos.org.au/facilities/srs/oceancolour/

Ocean colour data is produced from MODIS (Figure 3), VIIRS and Sentinel-3 sensors. The production of ocean colour data on the NCI provides users with the full suite of ocean colour products at three levels through the processing chain, enabling their use in a wider range of applications.

Copernicus Australasia (http://www.copernicus.gov.au/) is a regional hub as part of a collaboration between the Australian Government and the European Commission, providing open access to data from Europe's Sentinel satellite missions for the South-East Asia and South Pacific region. This data can be accessed via the NCI and through the Sentinel Australasia Regional Access (SARA) interface (https://copernicus.nci.org.au/sara.client/#/home). In an ocean colour context, Sentinel-3 Level 2 Water data products (OL_2_WFR) produced by ESA provide a range of derived ocean colour variables including Chl-a and total suspended sediment (https://sentinel.esa.int/web/sentinel/user-guides/sentinel-3-olci/product-types/level-2-water). The Australian Sentinel-3 Validation Team (S3VT) is an ongoing program within the Australian earth observation community to validate these products and quantify their accuracy in Australian waters (https://www.eoa.org.au/s3vt-oc).

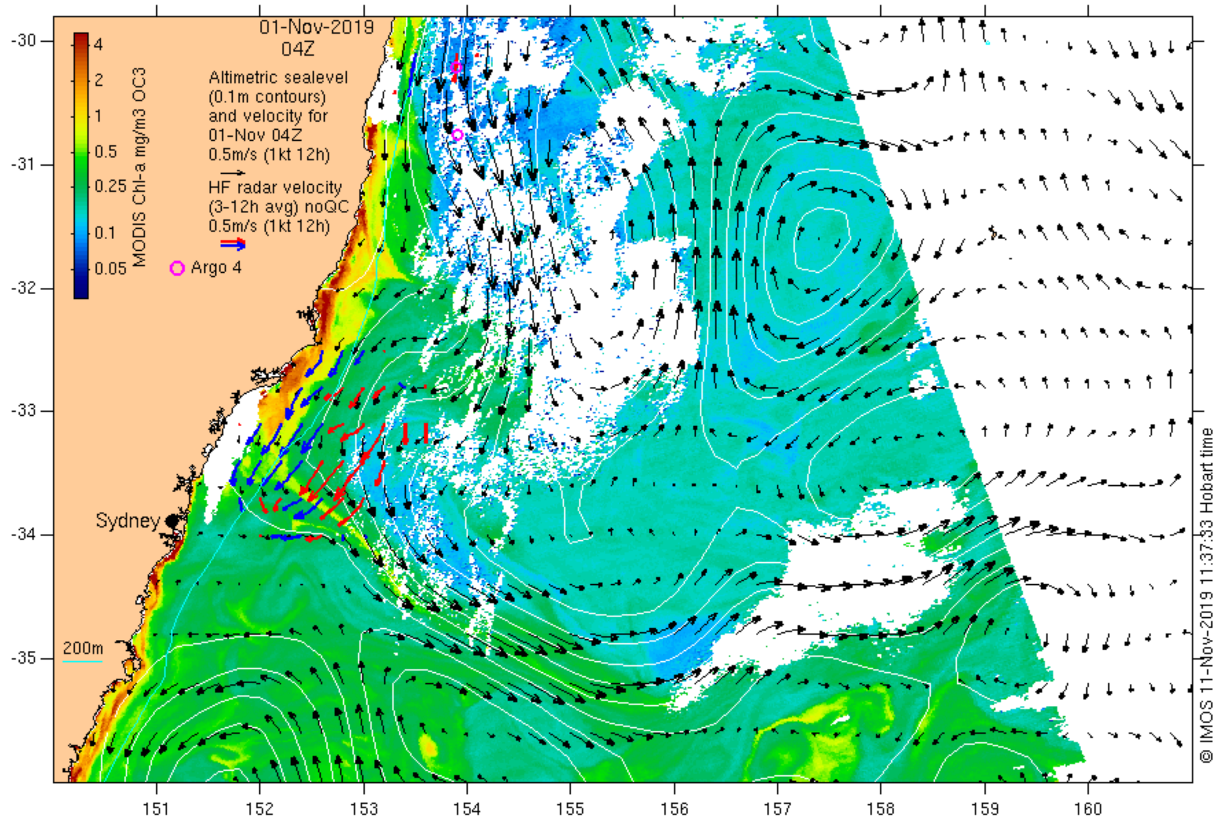


Figure 3 – Example of a daily composite Chl-a MODIS product off the coast of NSW, produced and delivered by the IMOS Satellite Remote Sensing Facility via the IMOS OceanCurrent portal (http://oceancurrent.imos.org.au)

2.2 Sea Surface Temperature

Zhi Huang (GA)

Sea Surface Temperature (SST) is one of the Essential Climate Variables defined by GCOS (Global Observing System for Climate) and is a key indicator of the climate system and ocean environment that helps quantify ongoing climate change (Merchant et al., 2012). In this section, we briefly describe:

- the basics of the SST observed by the Earth Observation (EO) Satellites,
- the value of satellite-derived SST data for the management and monitoring of marine protected areas (MPAs) and the broader marine estate, and;
- existing international and Australian activities, and satellite-derived SST data sources in Australia that are relevant to the management and monitoring of the Australian Marine Parks (AMPs).

2.2.1 General Background

SST can be defined as the water temperature within the mixed layer (approximately the upper 10 m) of the ocean surface (Beggs, 2019; Merchant et al., 2019). Minnett et al., (2019) defined five SST variables with increasing depths:

- Interface SST – the water temperature at the air-sea interface,
- Skin SST – the water temperature at a depth of ~10-20 µm,
- Subskin SST – the water temperature at the base of the conductive laminar sub-layer of the ocean surface,
- SST at depth – water temperature beneath Subskin SST at a specific depth, and
- Foundation SST – the water temperature free of diurnal temperature variability (approximately 10 m depth under calm conditions.

All the above SST variables, except for Interface SST, can be directly measured using in-situ instruments. Remotely, the EO satellites are able to detect emissions or thermal radiation of the Earth's surface in the wavelength ranges of middle infrared (3-8 µm), thermal infrared (8-15 µm) and microwave (1-300 mm). The infrared sensors on-board EO satellites, however, are only able to directly estimate Skin SST; while the passive microwave sensors are able to estimate Subskin SST (Chassot et al., 2011; Beggs, 2019; Merchant et al., 2019). Nevertheless, Foundation SST products are sometimes produced by choosing the Skin SST measurements at locations of high surface mixing (Griffin et al., 2017).

The thermal radiation received by EO sensors needs to be processed and calibrated to obtain Skin SST measures. This section only describes the key processing (or retrieval) steps of satellite SST from the infrared sensors because SST data derived from the microwave sensors currently have much less usage in the management and monitoring of AMPs.

The radiance measured by the infrared sensors, in other words the raw (or Level 0) data, needs to undertake several calibration and correction steps to retrieve accurate Skin SST measurements (e.g. Esaias et al., 1998; Chassot et al., 2011; Kilpatrick et al., 2015; Beggs, 2019; Merchant et al., 2019). The four key steps are:

1. Geolocation of image pixels,
2. Radiometric correction that converts measured radiance to top-of-atmosphere brightness temperature (Level 1),
3. Land and cloud masking, and
4. Atmospheric correction that removes atmospheric influence (e.g., absorption and scattering) to obtain Skin SST (Level 2).

The conversion of measured radiance to top-of-atmosphere brightness temperature is routinely conducted through the inversion of Plank's law (Chassot et al., 2011; Merchant et al., 2019). Strict land and cloud masking are needed to eliminate contaminated pixels (Beggs, 2019). Currently, the most widely used cloud screening algorithm is the probabilistic based approach proposed by Merchant et al., (2005) (Beggs, 2019). Above all, atmospheric correction is the most important calibration step for the accurate retrieval of Skin SST. A basic linear SST algorithm is written as:

$$SST_{ij} = a_0 + a_i T_i + a_j T_j$$

Where SST_{ij} is the derived Skin SST, T_i and T_j are the brightness temperatures in two selected infrared channels i, j, and a_0, a_i, and a_j are coefficients that need to be determined by using in-situ measurements or radiative transfer modelling (Beggs, 2019; Esaias et al., 1998; Kilpatrick et al., 2015; Merchant et al., 2019). Modifications to the linear algorithm by taking into account the limitations of linearity (i.e., non-linear SST algorithms) have also been implemented (e.g., Esaias et al., 1998; Kilpatrick et al., 2015; Merchant et al., 2019). Fundamentally, these SST algorithms rely on the association between differences in measurements in different sensor channels and the effect of atmosphere in one of them (Merchant et al., 2019).

2.2.2 SST for the Management and Monitoring of MPAs

Remotely sensed SST is one of the important environmental baseline variables for the effective management and monitoring of MPAs (Maxwell et al., 2014). SST is a key indicator in Australia state of environment reporting (Evans et al., 2017). Along with other remotely sensed variables such as Chlorophyll-a, satellite SST data are often used to characterise the pelagic environment and inform the design and management of MPAs (e.g. Devred et al., 2007; Chollett et al., 2012; Krug et al., 2017; Roberson et al., 2017; McIver et al., 2018). Satellite SST data are valuable in the study of marine ecosystem functions and the monitoring of marine biodiversity (Palacios et al., 2006; Secades et al., 2014). In the pelagic environment, biodiversity hot spots with high productivity and diversity are often associated with distinct oceanographic features such as ocean fronts, upwelling, and currents/eddies (Chassot et al., 2011; Hobday and Hartog, 2014). This is mainly because these oceanographic features are able to entrap and enrich nutrients from either adjacent or deep waters. Satellite SST data have demonstrated capability in the accurate identification and mapping of ocean fronts (Belkin et al., 2009; Bogazzi et al., 2005; Miller et al., 2015), coastal upwelling (Kuo et al., 2000; Huang and Wang, 2019) and ocean currents/eddies (Huang and Feng, 2015).

SST is an essential variable to characterise climate variability (Evans et al., 2017; Wijffels et al., 2018). For example, satellite-derived SST data have been used to study the decadal SST trends at the Australian and global scales (Foster et al., 2014; Hartmann et al., 2013; Dunstan et al., 2018; Wijffels et al., 2018). In addition, SST data can be used to identify and characterise extreme Marine Heat Wave (MHW) events (Hobday et al., 2016; Hobday et al., 2018). Such MHW events have significant impact on the marine ecosystems and the fishing industry, including coral bleaching (Eakin et al., 2010; Selig et al., 2010; Heron et al., 2016; McClanahan, 2017), altering of species distribution patterns (Smale and Wernberg, 2013; Wernberg et al., 2013), and economic impact in fisheries industry (Mills et al., 2013). In the later section, we present a case study using satellite-derived SST data to identify, characterise and map MHW events at the Lord Howe Marine Park.

SST data have also been used to help manage fisheries at sustainable levels (Stuart et al., 2011; Klemas, 2013). Satellite SST data, in conjunction with other remotely sensed data, offer a number of benefits for the effective management of fisheries resources (Yentsch, 1973; Chassot et al., 2011; Stuart et al., 2011; Klemas, 2013; Payne et al., 2017), including (but not limited to):

- Stock assessment,
- Habitat mapping of commercial species at different life-stages,
- Monitoring of habitat changes,
- Detection of harmful events such as algal blooms and MHWs, and
- Bycatch reduction.

For example, SST data are often used to identify ocean fronts, upwelling areas and eddies that are known to be associated with fish aggregation (Chassot et al., 2011; Hobday and Hartog, 2014). Similarly, SST data have been used to model and forecast habitats of important commercial species such as southern bluefin tuna and sardine (Eveson et al, 2015; Hobday et al., 2011; Payne et al., 2017). In additional to the benefits to fisheries management, SST data have helped characterise and monitor the spatial habitats and migration patterns of some iconic conservation species such as blue whales, humpback whales and loggerhead turtles (Hazen et al., 2017; Payne et al., 2017; Thums et al., 2017).

2.2.3 International and Australian SST activities and data sources

Increasingly, near real-time and forecast SST data have been used in operational platforms to describe and predict the physical state of the ocean (Payne et al., 2017). These operational tools offer great value in the effective management of marine resources and biodiversity. Table 3 lists a number of these operational tools in Australia and other parts of the globe. For example, the WhaleWatch and TurtleWatch tools developed by NOAA predict the habitat preference of blue whales and loggerhead turtles based on their preferred SST ranges (Hazen et al., 2017). Both operational tools are used by the fisheries industry to help reduce human impacts such as ship strikes, entanglements and bycatch on these conservation species.

NOAA has also developed the widely used Coral Reef Watch tool that uses SST data to provide current reef environmental conditions and to predict the likelihood of coral bleaching up to four months in the future (Strong et al., 2011; Liu et al., 2012, 2013).This tool is greatly benefited from several-decades' of continuous satellite observation of SST at global scales and increasingly accurate SST forecast by the new generation climate models. By estimating heat stress, the Coral Reef Watch tool is able to broadcast early warning and alert messages for coral reefs around the globe. The current version 3.1 of this global Coral Reef Watch tool uses global, 5 km resolution, daily SST data (Liu et al., 2017);

https://coralreefwatch.noaa.gov). In Australia, a similar methodology has been used in the ReefTemp Next Generation tool (Garde et al., 2014). The near real-time operational tool was the result of the collaboration between the BOM, CSIRO and GBRMPA that provides information on coral bleaching risk for the GBR region. The SST data used in the ReefTemp Next Generation tool are high-resolution (~2 km) daily (with gaps) and 14-day composited (near gap-free) night-time SST data from selected IMOS SST data sources. Because these SST data have been calibrated to the Australian region, they are more accurate and higher in spatial resolution than their global counterpart.

In addition, a tool has been developed and operationalised by Australian Fisheries Management Authority to map the Southern Bluefin Tuna (SBT) zone of the south-eastern margin (Hobday et al., 2011). The tool is used to help manage the SBT quota and enforce relevant SBT fishing regulations. The tool is based on the fundamental principle that SBT is observed to prefer a SST range that can be mapped in the observed and forecast SST data. A similar principle has been used to develop the SBT habitat forecasting tool in the Great Australian Bight (Eveson et al., 2015). Both tools have been used by fisheries management authorities and the fisheries industry for the sustainable management of the SBT, a highly important commercial species.

For the oceans surrounding the Australian continent, there are several accurate and high-resolution satellite-derived SST data specifically developed by the BOM and CSIRO for the Integrated Marine Observing System (IMOS) (Beggs, 2019). The IMOS SST data cover a period of more than 25 years since 1992. Table 4 lists a number of such SST datasets and their main characteristics, with more details in Beggs (2019). The AVHRR (Advanced Very-High-Resolution Radiometer) SST data span several NOAA POES (Polar Orbiting Environmental Satellite) and ESA MetOp missions. Global, 4 km (at nadir) resolution AVHRR SST data are available back to 1981 from NOAA and the ESA Climate Change Initiative (CCI). However, over the Australian region IMOS provides higher spatial resolution (~1.1 km at nadir) AVHRR SST data back to 1992 in widely used GHRSST (Group for High Resolution SST) formats, with error estimates for each pixel. AVHRR sensors provide the most widely used SST data around the world and in Australia.

The VIIRS (Visible Infrared Imaging Radiometer) SST data is the new generation SST data, with higher native resolution (0.75 km vs 1.1 km at nadir), greater spatial coverage and better accuracy than those of the AVHRR. The IMOS Multi-Sensor SST composites (“Level 3”) are formed from blending AVHRR and VIIRS SST data from several satellites over a regular 2 km x 2 km grid. As a result, they have better spatial coverage and accuracy compared with IMOS composites of only AVHRR or VIIRS SST (Beggs, 2019). The new generation of IMOS multi-sensor Level 3 SST data are being developed to incorporate SST data from additional sources and are expected to have further improved spatial coverage and accuracy.

The IMOS MODIS (Moderate Resolution Imaging Spectroradiometer) Level 3 SST data, gridded over 1 km x 1 km, have higher spatial resolution than that of the 2 km AVHRR Level 3 SST, but somewhat lower spatial coverage due to their slightly narrower swath width (2330 km cf 2700 km). Also, they do not comply with the GHRSST standard and their accuracy has not been specifically calibrated using in-situ data in the Australian region. However, one advantage of MODIS SST data is that the SST observations are exactly simultaneous with the other ocean-colour variables derived from the MODIS sensor which indeed offers unique benefits in many marine applications (e.g., Dunstan et al., 2018; Huang and Feng, 2015; Huang and Wang, 2019).

Unlike the above-mentioned sensors on-board polar-orbiting platforms, The AHI (Advanced Himawari Imager) sensor on-board the Himawari-8 (H-8) satellite operated by the Japan Meteorological Agency (JMA) is on a geostationary platform (Bessho et al., 2016).The H-8 SST data thus offer frequent temporal snapshots (every 10 min) for the Australian region, with similar spatial resolution to the AVHRR SST data (Kurihara et al., 2016). As a result, the H-8 SST data provides great potential for investigating highly dynamic oceanographic and climate events such as upwelling and MHWs (e.g., Huang et al., (2018) and the case study in section 3.1)

Name	Area of Interest	Brief Description	URL	Key References
WhaleWatch	US West Coast	Prediction of where blue whales are likely to be in near real-time	https://www.westcoast.fisheries.noaa.gov/whalewatch/	Hazen et al. (2017)
TurtleWatch	Pacific Ocean north of the Hawaiian Islands	Prediction of the thermal habitat of loggerhead sea turtles	https://www.fisheries.noaa.gov/resource/map/turtlewatch	Howell et al. (2008, 2015)
Coral Reef Watch	Global	Identification and prediction of the areas at risk for coral bleaching	https://coralreefwatch.noaa.gov/satellite/index.php	Liu et al. (2003); Liu et al. (2006); Strong et al. (2011)
GAB Southern Bluefin Tuna Habitat Forecasting	Great Australian Bight	Prediction of habitat preferences of southern Bluefin tuna	http://www.cmar.csiro.au/gab-forecasts/	Eveson et al. (2015)
SE Australia Southern Bluefin Tuna zone	Southeast Margin	Location of the southern Bluefin tuna zone	https://www.afma.gov.au/fisheries-services/sbt-zones	Hobday et al. (2011)
GBR ReefTemp Next Generation	Great Barrier Reef	Prediction of coral bleaching risk	http://www.bom.gov.au/environment/activities /reeftemp/reeftemp.shtml	Garde et al. (2014)

Table 3 - The operational tools in International and Australian waters that use SST data

Platform/Sensor	Data Custodian	Data Access	Spatial Resolution	Temporal Resolution	Temporal Coverage
POES/AVHRR	IMOS	AODN	~ 2 km	daily, 3-day, 6-day, monthly	1992 - present
NPP/VIIRS	IMOS	AODN	~ 2 km	Twice-daily	2012 - present
Multisensor	IMOS	AODN	~ 2 km	Daily, 3-day, 6-day, monthly	2012 - present
H-8/AHI	IMOS, JAXA	BOM, JAXA	~ 2 km	hourly, daily, monthly	2015 - present
Aqua/MODIS	IMOS	AODN	~ 1 km	Daily, monthly	2002 - present

Table 4 - L3 SST products covering the Australian region

2.3 Shallow and Coastal Waters

Stephen Sagar (GA)

Australian Marine Parks (Commonwealth reserves proclaimed under the EPBC Act in 2007 and 2013) are located in Commonwealth waters that start at the outer edge of state and territory waters, generally three nautical miles (approximately 5.5 km) from the shore, and extend to the outer boundary of Australia's exclusive economic zone, 200 nautical miles (approximately 370 km) from the shore. Although this places most coastal and shallow water environments in state jurisdictions, there are many off-shore reefs and islands within Australia's Commonwealth MPAs (eg see Botha et al., 2010), as well as the world heritage listed Great Barrier Reef, managed through the Great Barrier Reef Marine Park Authority (GBRMPA).

Earth Observation is widely used to map, monitor and assess coastal and shallow water environments (Cannizzaro and Carder, 2006; Phinn et al., 2008; Vahtmäe, 2009; Lyons et al., 2012; Botha et al., 2013; Hedley et al., 2016). There are however fundamental differences in the sensors, methods and algorithms that can be effectively utilised in these regions in comparison to open ocean pelagic remote sensing. One of the primary differences is the scale of the features that are of interest. In shallow waters and coastal regions, mapping of benthic habitats and coastal features requires a resolution at the metre to 10's of metres scale, far beyond that offered by the current generation of ocean colour sensors. Whilst there are a range of public and commercial satellites and sensors that offer this scale of analysis (Table 5) many of these are designed for terrestrial applications and the trade-off is often a decrease in spectral resolution and sensitivity.

These higher resolution public good sensors have still been extensively used for coastal and shallow water applications, and shown to have capabilities including monitoring water constituents (Braga et al., 2016; Pahlevan et al., 2019), mapping benthic habitats and deriving bathymetry (Hedley et al., 2012) and mapping coastlines and intertidal regions (Murray et al., 2012; Sagar et al., 2017). In the following sections we introduce a selection of these applications and highlight some of the particular issues that must be considered when dealing with complex coastal and shallow waters.

2.3.1 Shallow water applications

Shallow water in the context of remote sensing is generally considered to be regions which are 'optically shallow'; where light reflected from the sea-floor contributes to the light measured back at the sensor. In practice, this can be a variable depth ranging from less than 1 metre in highly turbid waters where the light is fully absorbed and scattered by the high concentrations of constituents in the water column before it reaches the seafloor, up to over 30 metres in clear coral waters.

Sensor Resolution	Platform	Sensor	Spatial Resolution = Pixel Size	Spectral Bands (400 - 1000nm)	Revisit Frequency (at equator)	Launch	Water Quality Variables						Macrophytes, macro-algae, seagrasses and corals			Shallow Water Bathymetry
							Chl	CYP	TSM	CDOM	Kd	Turb / SD	Emergent	Floating	Submersed	
Mid	Terra/Aqua	MODIS-A&T	500m	2	Daily	1999/ 2000	3	4	2	3	3	3	4	3	3	3
	Terra/Aqua	MODIS-A&T	250m	2	Daily	1999/ 2000	3	4	2	4	3	3	3	3	3	3
	Sentinel 3 A/B	OLCI	300m	21	daily (with 2 satellites)	2016/ 2018	1	1	1	1	1	1	1	1	1	1
Mid - High	Landsat 8	OLI	30m	5	16 days	2013	2	S	1	2	1	1	2	2	2	2
	Sentinel 2 A/B	MSI	10 - 60m	10	5 days	2015	2	S	1	2	1	1	2	2	2	2
High	IKONOS, QuickBird, SPOT-5 , 6 GeoEye etc.		2-4m	3 to 4	Programmable: 60 days to 2–3 days	1999 onwards	3	S	1	3	1	1	2	2	2	2
	RapidEye		6.5m	5	Daily	2005	3	S	1	3	1	1	2	2	2	2
	Worldview-2		2m spectral - 0.5m B&W	8	Programmable: 60 days to 1 days	2009	2	2	1	2	1	1	1	1	1	2
	Worldview-3		1.24m spectral - 0.5m B&W	8	Programmable: 60 days to 1 days	2014	2	2	1	2	1	1	1	1	1	2
	PRISMA		20m spectral - 2.5m B&W	66	25 days / Pointing 7 days	2019	1	1	1	1	1	1	1	1	1	1

Table 5 - Current relevant earth observation platforms and sensors for coastal and shallow water applications modified from Groom et al. (2019) and CEOS (2018). 1 – Highly Suited, 2 – Suitable, 3 – Potential, 4 – Not suitable

In a shallow environment this contribution of light returned from the sea floor complicates the ability to retrieve or estimate the water column properties introduced in section 2.1. Algorithms designed for ‘traditional’ ocean colour retrievals and sensors do not factor in light reflectance from the seafloor, which is a function of both the depth (and constituents) of the water column and the type of benthic habitat. There are some promising approaches which attempt to constrain these confounding influences in shallow waters to enable the estimation of water column constituents (McKinna et al., 2015) and benthic photosynthetically active radiation (PAR) (Magno-Canto et al., 2019); developed in case studies across the GBR using MODIS. However, these approaches require a known depth model and reasonable approximation of benthic reflectance (or albedo) which can restrict their wider application.

Having a signal from the seafloor does however open up a range of other applications for assessing and monitoring these shallow habitats. In shallow water, remote sensing has been used to map and monitor benthic habitats (Andrefouet et al., 2003; Kutser et al., 2006; Goodman and Ustin, 2007; Klonowski et al., 2007), estimate water depth (Lee et al., 1998; Stumpf et al., 2003; Brando et al., 2009; Hedley et al., 2009), model water column properties (Barnes et al., 2018; Russell et al., 2019), and model the extent of coral bleaching events (Yamano and Tamura, 2004; Hedley et al., 2018; Skirving et al., 2018).

Similar to ocean colour applications, the algorithms used range from empirical image based versions, which generally leverage existing knowledge to create a band based relationship, through to physics-based or semi-analytical versions which seek to characterise the radiative transfer model for how light interacts within the shallow water environment (see Dekker et al., 2011). Empirical methods can be effective in study areas where in-situ data, such as depth, can be used to develop a model, however they lack transferability between locations and time-steps, which make them a poor choice for monitoring applications. The repeatability of physics-based methods, and the fact that they do not require in-situ data, has meant that they have had a broader uptake for ongoing shallow water habitat and bathymetry mapping. There is a large manner of ways in which the physics-based radiative transfer model problem is tackled, from look-up tables (LUTs) which populate a database of multiple environment scenarios to model from (Mobley et al., 2005; Hedley et al., 2009), optimisation methods which iterate through environmental parameter values to fit a model to the observed remote sensing data (Lee et al., 1999; Brando et al., 2009), through to methods which holistically model the full shallow water and atmospheric system (Cerdeira-Estrada et al., 2012). The user does however need to be aware that although these methods do not explicitly require in-situ data, many require a degree of knowledge about the optical water type being examined and the types of substratum likely to be encountered for them to be applied most successfully.

Many of these methods have been developed, both theoretically and practically, on hyperspectral (often airborne) sensors. From a cost and logistics perspective, these sensors are not feasible for monitoring applications, and much work has been completed in assessing and modifying these methods for application to multi-spectral earth observation data. In an MPA monitoring context, Botha et al., (2010) demonstrated the potential of a physics-based method, utilising the commercial Quickbird sensor over off-shore reefs in the Coral Sea to map bathymetry and habitat classes (Figure 4 – Example of habitat mapping using the high resolution commercial Quickbird sensor for the Western portion of Elizabeth Reef, Coral Sea. For further details see Botha et al. (2010).). However, use of commercial sensors is still likely cost-prohibitive to establish suitable monitoring programs. In recent years, the launch of the

Sentinel-2 satellites, with a joint revisit time of 5 days, have shown great potential to fill the gap between the spatial resolution of commercial sensors such as World-View 2 and the spectral resolution of hyperspectral sensors.

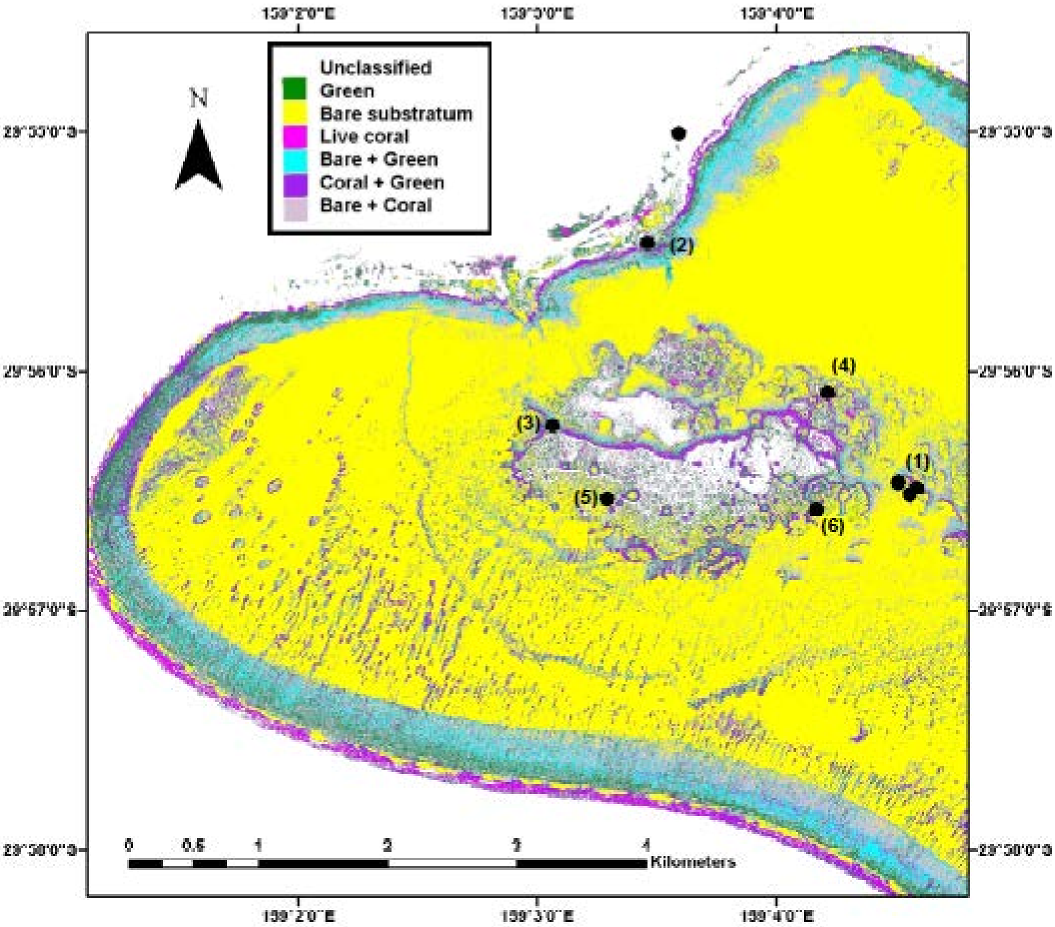


Figure 4 – Example of habitat mapping using the high resolution commercial Quickbird sensor for the Western portion of Elizabeth Reef, Coral Sea. For further details see Botha et al. (2010).

Recent work in the GBR has shown the potential for integration of ancillary datasets to tailor and improve the outputs that can be generated from remote sensing data (Roelfsema et al., 2018). The GBR project draws on benthic reflectance and depth maps generated from Sentinel-2, in conjunction with other ecological models and data (such as wave exposure and geomorphic classifications). As a result of this integrated workflow, improved benthic composition and geomorphic zone maps were able to be produced over an area of ~2500km^2, much larger than previous coral reef habitat mapping studies. This kind of example is an illustration of the value of using remote sensing outputs as a complementary data set alongside other tools and data in a monitoring and mapping context.

2.3.2 Coastal water applications

Coastal waters are subject to a range of environmental and estuarine influences not present in oceanic waters, including the increased re-suspension of sediments from waves or tides, and the presence of increased levels of coloured dissolved organic matter and sediments from river run-off. The optical complexity of these coastal waters means that the assumptions that underpin the standard (global) products and algorithms from ocean colour sensors (generally that absorption and scattering is primarily from chlorophyll and sea water), are not valid. Additionally, atmospheric correction methods designed for oceanic waters have been shown to produce poor results in optically complex coastal regions (discussed further in section 4.1.3).

This means that alternative approaches are required, which characterise the full range of constituents present in complex coastal waters. One example of such an approach implemented within the Australian eReefs project focussing on the Great Barrier Reef, is the coupling of two physic-based inversion algorithms, one performing atmospheric correction, and one the subsequent water quality retrieval (Schroeder et al., 2007; Brando et al., 2012). The eReefs atmospheric correction has been implemented based on inverse modelling of radiative transfer simulations in a coupled ocean-atmosphere system using artificial neural networks (ANN). The atmospherically corrected reflectance at mean sea level is then provided as input the water quality algorithm, which uses an adaptive Linear Matrix Inversion (aLMI).

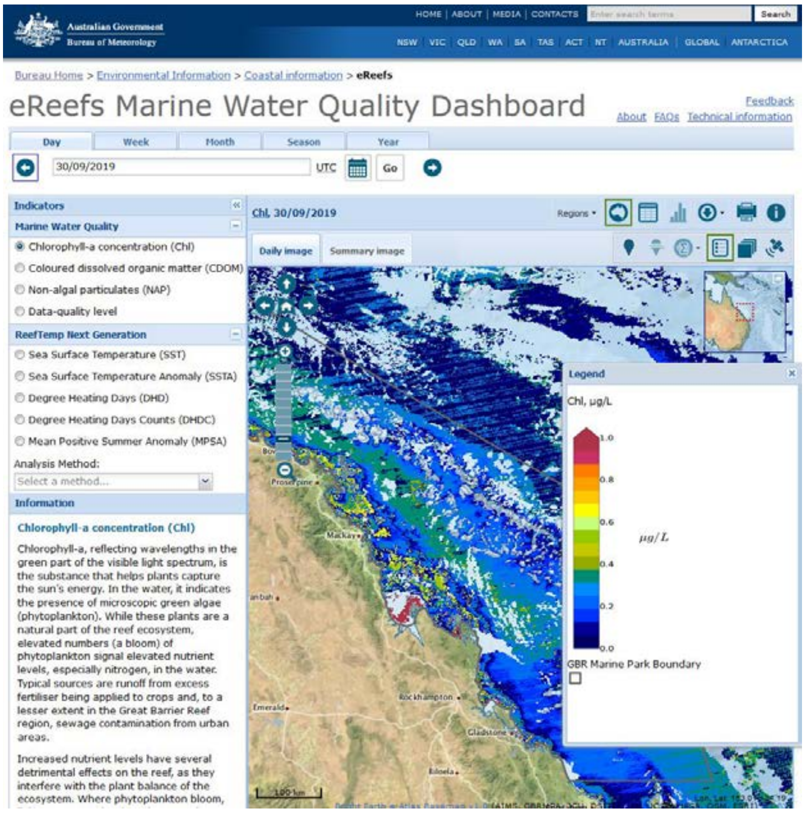


Figure 5 – The eReefs Marine Water Quality Dashboard – Daily Chl-a estimated from MODIS using the aLMI algorithm (Brando et al. 2012)

The aLMI method is an inversion approach, which considers a selected range of regional inherent optical water properties (e.g. absorption and scattering) obtained from field measurements and retains the one most representative set of optical water properties being examined, to estimate a range of water column parameter concentrations including chlorophyll-a, non-algal particulates and CDOM absorption. This approach enables multiple water types within a single image to be accounted for consistently. This ANN-aLMI algorithm approach enables multiple sets of inherent optical properties within a single image to be accounted for consistently.

With appropriate parametrisation, this allows the algorithm to be deployed in operational monitoring programs such as eReefs in the GBR and provide daily water constituent concentration data to underpin a range of applications. In 2013 the ANN-These data are provided operationally via the Marine Water Quality dashboard (http://www.bom.gov.au/marinewaterquality/) (Figure 5). Currently however this portal does not provide high quality data as sensor calibrations are not kept up to date by BoM due to limited resources. More up-to-date and recently calibrated ANN-aLMI data can be obtained directly from CSIRO.

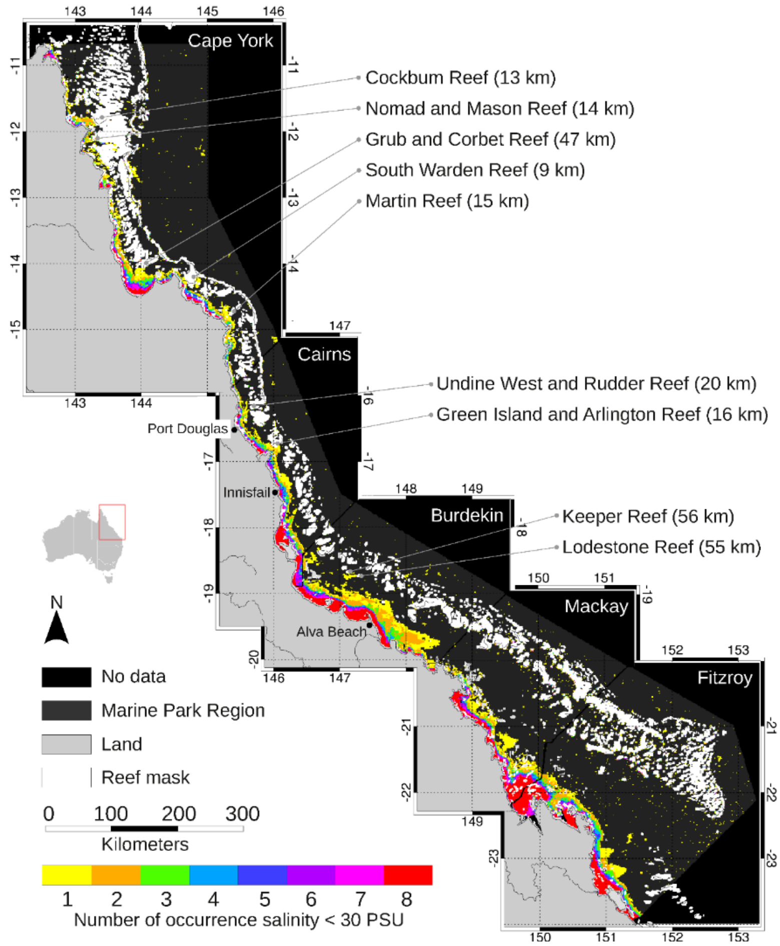


Figure 6 - Frequency of freshwater extent based on the inverse relationship of terrestrial CDOM and salinity: salinity less than 30 PSU for eight wet seasons between 2003 and 2010 (Schroeder et al., 2012).

In addition to the application of ocean colour sensors, the new generation of publicly available high resolution sensor data (Landsat 8, Sentinel-2) have be shown to have great potential in mapping suspended sediments and turbidity (Nechad et al., 2010; Dogliotti et al., 2015). One of the benefits of working with higher resolution data in mapping phenomena such as turbidity, is the ability to spatially map the historical pattern and movement of plumes from flood events or anthropogenic pressures such as dredging (Vanhellemont and Ruddick, 2014; Brando et al., 2015). In Australia, there has also been considerable success in utilising medium resolution ocean colour data to map river plumes, freshwater extents and their effects over the GBR (Brodie et al., 2010; Schroeder et al., 2012) (Figure 6) and impacts on turbidity and suspended sediments from dredging in the Kimberley, WA (Dorji et al., 2016; Dorji and Fearns, 2017).

COST VS SCALE VS REVISIT – WHAT DATA TO USE?

One of the biggest challenges in determining the most suitable earth observation data set for an application is weighing up the pros and cons in terms of spatial, temporal and spectral resolution, and this is particularly the case in coastal environments. In tables 2 and 5 we have summarised commonly used sensors for oceanic and coastal remote sensing. As can be seen in these tables, and a rule of thumb for remote sensing in general, there is a trade-off between characteristics of each sensor. For increased re-visit frequency, often spatial resolution is sacrificed; and when increasing spatial resolution, often this comes at a cost of spectral resolution, or the number of bands measured by the sensor. This has a profound impact on the types of applications that can be tackled by each sensor, and although these traditional barriers are beginning to be broken down (e.g. Sentinel-2), they are still a primary consideration when considering monitoring applications from remote sensing.

Another important consideration is the cost of data. The temptation for many mapping purposes is to acquire the highest resolution data possible, so as to map with as high detail as possible, and in some applications this may be essential. However, high resolution (<5m) data is predominately commercial in nature, and can cost in the range of $5-40USD per sq km. In terms of monitoring, this cost makes it prohibitive for ongoing use, and often the re-visit time for these sensors is on an ad-hoc or on-request basis (for an additional fee). Careful consideration of the needs and end goals of an application is recommended for managers. Often a combination approach may be optimal, for instance, developing a baseline map from high resolution data and monitoring program from open access data. With the arrival of the new generation of sensors such as Sentinel-2, this resolution gap is closing, and most applications in a marine context can be addressed with freely available public data.

3. EARTH OBSERVATION TO DETECT AND MONITOR HUMAN INDUCED PRESSURES

The application of earth observation data and science offers the potential to inform on a range of human induced pressures on the marine environment. Many effects of these pressures are relevant to MPA management, and remote sensing can provide information ranging from detecting the source of the pressure, through to ongoing monitoring of the spatial and temporal extents of the impact. In this section we present a selection of case studies across different human-induced pressures and discuss the range of earth observation data types and analysis that can be used to examine them.

3.1 Marine Heat Waves

Zhi Huang (GA)

3.1.1 Background

Extreme climate events have received increasing attention due to the intensification of weather extremes in recent years (Jentsch et al., 2007). A Marine Heat Wave (MHW) is such an extreme event, defined as a prolonged discrete anomalously warm water event (Hobday et al., 2016). In recent years, intense MHWs have occurred around the world including in Australian waters (Olita et al., 2007; Feng et al., 2013; Mills et al., 2013; Pearce and Feng, 2013; Chen et al., 2014; Bond et al., 2015; Di Lorenzo and Mantua, 2016). MHWs have significant impact on the coastal/marine ecosystems and fisheries. Coral bleaching is the most published consequence of MHWs (Eakin et al., 2010; Selig et al., 2010; Heron et al., 2016; McClanahan, 2017). However, MHWs can also have significant impact on other marine species by causing mass mortality and changing species distribution. For example, the 2010-11 Western Australia MHW event has significantly altered the biodiversity patterns of temperate seaweeds, sessile invertebrates and demersal fish (Smale and Wernberg, 2013; Wernberg et al., 2013). Fish kills and sightings of some iconic species such as whale sharks and manta rays outside their normal ranges have also been reported after this unprecedented event (Pearce and Feng, 2013). The 2012 NW Atlantic MHW has led to an economic crisis in the lobster fishery (Mills et al., 2013). A mass scallop mortality event towards the latter half of 2010 in Bass Strait may also be related to an earlier MHW event (Przeslawski et al., 2018). Consequently, there is a pressing need to identify the temporal and spatial patterns of MHWs, examine their underlying mechanisms, and investigate their ecological impacts. Currently, several online applications have been set up to specifically help coral reef monitoring and management, including NOAA's Coral Reef Watch on a global scale (Liu et al., 2003; Liu et al., 2006; Strong et al., 2011) and BOM's ReefTemp Next Generation for the GBR region (Garde et al., 2014). These applications, however, lack the spatial extent, content and detail that are needed as a decision support tool for the management of vast areas of Marine Parks.

3.1.2 Lord Howe Marine Park case study

Long-term time-series SST data are needed to identify MHW events. This case study used the following satellite-derived SST datasets to identify and characterise the MHW events in the Lord Howe Marine Park:

- IMOS daily MODIS SST dataset between July 2002 and Oct 2018,
- JAXA night-time daily H-8 SST dataset between Aug 2015 and Feb 2019, and
- SSTAARS climatology dataset that is based on 25-year IMOS night-time AVHRR SST data (Wijffels et al., 2018).

The case study has two components:

1. Using the MODIS SST dataset to examine the historical MHW events in the Lord Howe Marine Park for the past 16 years, and
2. Using the H-8 SST and SSTAARS datasets to identify, map and characterise the MHW events in the Lord Howe Marine Park for the last three and half years.

Following Hobday et al. (2016), MHW is defined as a prolonged discrete anomalously warm water event with the following characteristics:

- Lasts for five or more days,
- SST warmer than the 90th percentile based on a historical baseline (or baseline climatology), and
- With well-defined start and end times.

In the first component of this case study, the 90th percentile climatology was directly calculated from the 16-year MODIS SST data. In the second component of this case study, we used the 90th percentile climatology data contained in the SSTAARS dataset.

According to the MODIS SST data, in the past 16 years, MHW events have been active on approximately 2400 days in some part of the Lord Howe Marine Park, which represents 40% of the data period. However, there was large temporal variability of the MHWs (Figure 7). Four most notable periods of relatively prolonged and intense MHWs (Figure 7) include:

1. In the autumn of 2004, the marine park recorded a mean MHW intensity of 0.70 ^{o}C per day above the 90th percentile climatology for 60 days; while, in the winter that followed, nearly every day was identified as a MHW day (e.g., 87 out of 92 days).
2. The period between 2009-10 summer and 2010 winter experienced the most prolonged and intense MHWs in the Lord Howe Marine Park, with mean intensity up to 0.80 ^{o}C per day above the 90th percentile climatology and a total duration of 226 out of 274 days.
3. In 2015 spring, 2016 autumn and 2016 winter, the marine park again experienced notable MHWs, with mean intensity of 0.78 ^{o}C per day in 2015 spring and a duration of 83 days in 2016 autumn.
4. The three continuous seasons starting 2017-18 summer saw another period of relatively prolonged and intense MHWs, with mean intensities of 0.51-0.70 ^{o}C per day above the 90th percentile climatology and durations of 51-65 days.

It should be noted that two of these four periods coincided with moderate to strong El Niño years – 2009-10 and 2015-16 according to BOM (http://www.bom.gov.au/climate/enso/enlist/index.shtml) and NOAA (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php; https://ggweather.com/enso/oni.htm). Year 2003-04 was a weak El Niño year according to NOAA; while, 2017-18 was a weak La Niña year according to BOM and NOAA. We also noticed significant spatial variability of the MHWs in the Lord Howe Marine Park. Within the marine park, between 0-18% of the area observed by the MODIS data were affected by the MHWs (Figure 7). However, large data gaps often occur in the daily MODIS SST data due to cloud coverage which poses a significant challenge for the accurate investigation of MHWs' spatial variability.

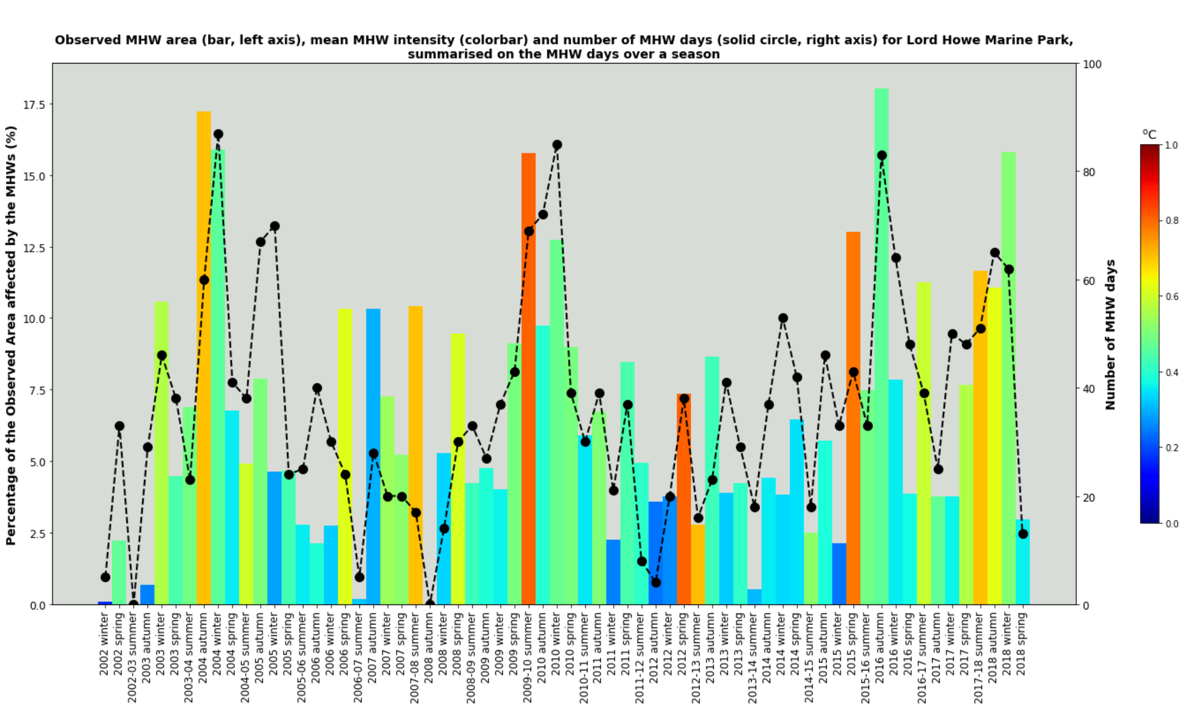


Figure 7 - The seasonal variation of the MHW characteristics for Lord Howe Marine Park identified using MODIS SST data. The MHW area is calculated as the percentage of the marine park observed by MODIS SST data. The mean MHW intensity is represented as degrees above the 90th percentile climatology calculated from the daily MODIS SST data between July 2002 and October 2018. The MHW days indicate the number of days for which the marine park has been affected by MHWs.

The H-8 SST data have much improved coverage benefiting from the very high temporal frequency (Bessho et al., 2016). This renders them the ideal data to investigate the high spatial and temporal heterogeneity of MHWs (Lima and Wethey, 2012; Scannell et al., 2016). The case study using the H-8 SST data showed that in the past three and half years, between Aug 2015 and Feb 2019, there were 14-39 MHW events of variable durations occurring in and around the Lord Howe Marine Park, with more events in the northern and southern parts of the marine park (8a). The total MHW days ranged from 186 to 504 days out of ~1400 total days, with similar spatial distribution to that of the number of events (Figure 8b). The total accumulated MHW intensities were of 109-503 °C, with much higher accumulated intensity in the southern part of the marine park (Figure 8c). A similar spatial pattern was identified for the overall mean MHW intensities, ranging 0.46-1.20 °C/per day (Figure 8d). The largest cumulative intensity occurred in a large part of the northern and southern marine park in the 2017-18 summer and 2018-19 summer, respectively (Figure 9a). The largest mean intensity occurred in the 2017-18 summer, 2017 spring and 2018-19 summer, in the northern, central and southern parts of the Lord Howe Marine Park, respectively (Figure 8d). Similarly, the MHW events with the highest intensity occurred in the 2017-18 summer, 2017 spring and 2018-19 summer, in the northern, central and southern parts of the marine park (Figure 9d). The MHW events with the longest duration most often occurred in the 2018-19 summer in the central part of the marine park (Figure 9c). The prolonged and intense 2018-19 summer MHW events affecting the Lord Howe Marine Park have resulted in coral bleaching observed in March 2019 and reported in The Conversation (http://theconversation.com/bleaching-has-struck-the-southernmost-coral-reef-in-the-world-114433) and The Guardian (https://www.theguardian.com/australia-news/2019/apr/01/lord-howe-island-coral-bleaching-most-severe-weve-ever-seen-scientists-say). Note that 2018-19 summer has seen weak El Niño activity according to NOAA's Oceanic Niño Index (ONI).

In summary, the MHW case study for the Lord Howe Marine Park indicates that:

- The MHW events have large temporal and spatial variability, able to be well characterised by the H-8 data.
- El Niño events tend to increase the duration and intensity of the MHW events (Heidemann and Ribbe, 2019).
- The MHW events occurring in summer are likely to cause coral bleaching.
- The MHWs also often occur in winter.

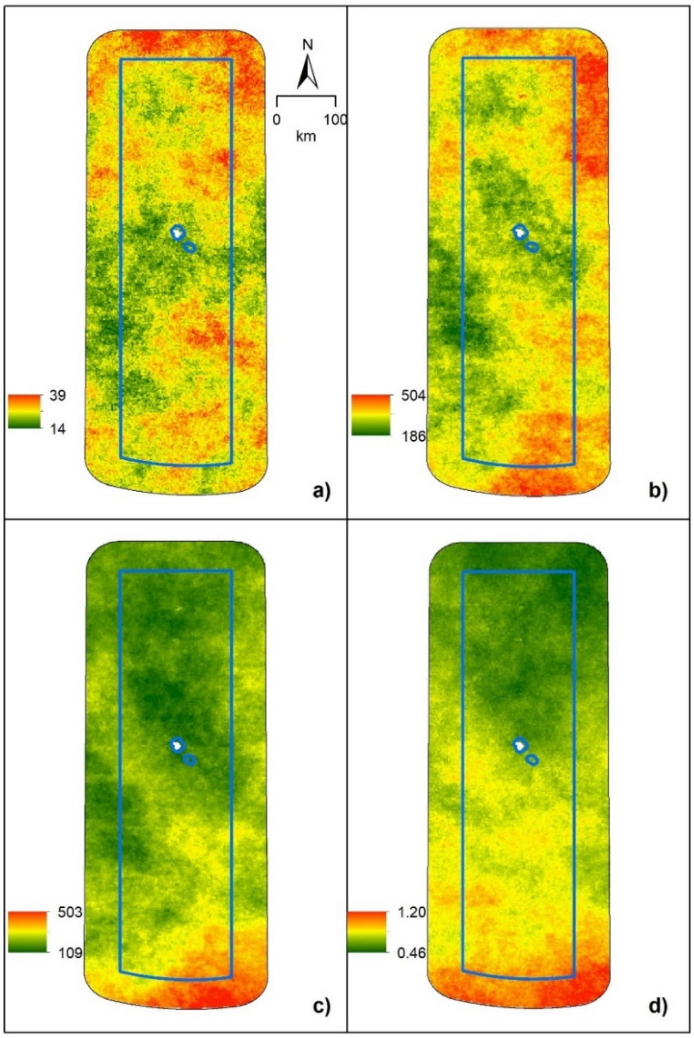


Figure 8 - Summary statistics of MHW events identified for Lord Howe Marine Park (Tasman Sea) using H-8 SST data, showing a) the number of MHW events; b) the total number of MHW days; c) the total MHW intensity (oC days); d) the mean MHW intensity (oC per day).

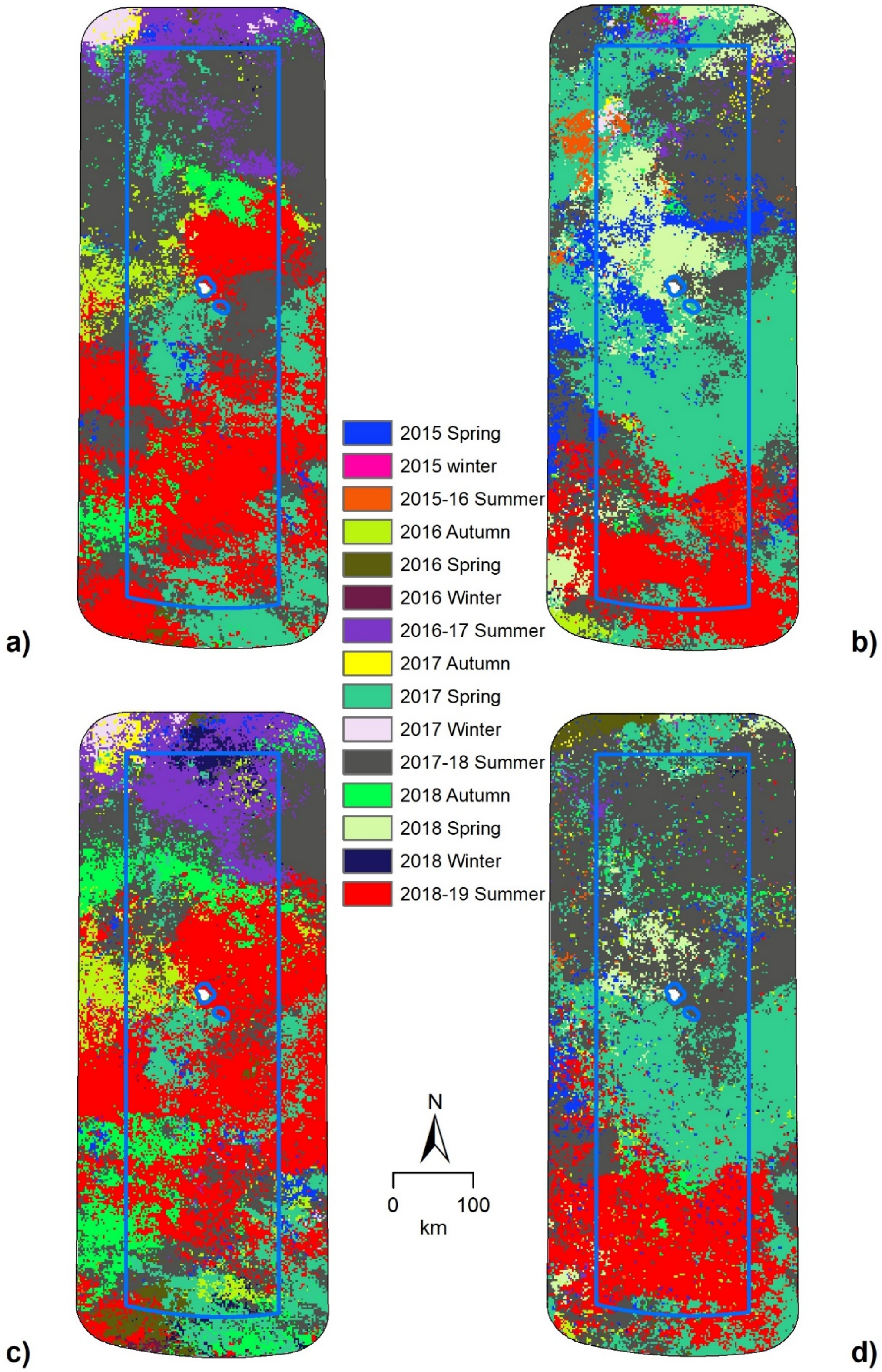


Figure 9 - Seasonal characteristics of MHW events identified for Lord Howe Marine Park (Tasman Sea) using H-8 SST data. a) the seasons with the largest cumulative intensity; b) the seasons with the highest mean intensity; c) the seasons with the longest duration; d) the seasons with the highest intensity.

3.2 Ship detection

Inke Falkner (GA)

3.2.1 Capabilities and platforms

Ship detection using satellite remote sensing imagery has an increasingly important role to play in marine safety and traffic surveillance and the exposure of illegal fishing activities and oil discharge offenders, particularly when vessel monitoring systems (VMS) and/or automated identification systems (AIS) are disabled or unavailable. Both optical sensing and synthetic aperture radar (SAR) data have been used to detect a range of vessels in coastal and off-shore environments (reviewed by Crisp, 2004; Kerbaol and Collard, 2005; Gens, 2008; Kanjir et al., 2018)

Synthetic Aperture Radar (SAR) has been the primary sensor for ship detection having the general advantage of being able to image during day and night and in most weather conditions with reasonable resolutions. SAR is particularly helpful in detecting ships as they are made of metal and have sharp edges, which reflect radar signals strongly. Even in the case of wooden boats, the engine, exhaust and propulsion are made of metal and can be detected. In an ideal case detected ships are visible as bright dots and geometric shapes on a darker surface. However, radar images have a fairly high level of intrinsic noise (speckle), which is worse in images taken during high winds and seas. In addition, false detections are difficult to recognise and small targets less than 10-15m are generally difficult to detect. However, the classification of ship type is challenging but can sometimes be achieved. Ship identification, on the other hand, remains impossible (Crisp, 2004; Corbane et al., 2010).

With the increased availability of high resolution optical satellite data, the number of maritime monitoring studies using these data has grown over recent years. However, accuracy of vessel detection using optical data remains greatly influenced by weather conditions including cloud cover and haze, solar angle and individual imaging sensor characteristics. Numerous algorithms have been developed to resolve these challenges with varying success and to develop fully automated detection systems that can deal with large volumes of data in near-real time (reviewed in Kanjir et al. 2018).

Different data types derived from optical sensors are used for vessel detection. Imagery collected in the visible and the near- and short-wave infrared are most commonly used due to their accessibility and accuracy in detecting and classifying vessels. An increasing number of scientists have also used satellite imagery obtained from Google Earth/Microsoft Virtual Earth in their research (Kanjir et al. 2018). These data are pre-processed and spatially inaccurate and therefore only moderately valuable, but they can be used as training or testing samples for machine-learning.

More recently, imagery captured with night-time optical sensors has been analysed for shipborne lights. In particular, fishing vessels with their bright nightlights have been detected successfully from space at night (Elvidge et al., 2015; Straka et al., 2015). The successful launch of the Suomi National Polar Partnership (SNPP) satellite housing the Visible Infrared Imaging Radiometer Suite (VIIRS) day/night band (DNB) sensor boosted the capability for satellite low light imaging. The sensor uses a bandwidth of 0.5 – 0.9 µm and with its high spatial resolution enables the detection of a large number of individual lighting features off-shore compared to previously (Miller et al., 2013; Schueler et al., 2013; Elvidge et al., 2015). The system works best in dark nights when illumination from the moon is low. The VIIRS data has one issue, which is its huge data volume (540MB) per aggregate compared to previous data types. This has so far limited the number of users of these data.

3.2.2 Application in MPA monitoring

In the context of MPA monitoring identifying fishing vessels that conduct illegal, unreported and unregulated (IUU) fishing within MPA boundaries, is of particular interest. Although current satellite data cannot be used to identify the owner/operator of the detected vessels, satellite data can be cross referenced with boat location data from VMS (vessel monitoring system) or AIS (automatic identification system) to identify boats that are not operating a location beacon (Oozeki et al., 2018).

The Australian Fisheries Management Authority (AFMA) monitors Commonwealth fishing vessels in order to detect illegal fishing activities (Appleyard, pers comms). Commonwealth fishing boats are tracked via satellite through their VMS, whereby vessels not operating a VMS may be ordered to return to port. VMS also alert vessel operators automatically when they enter protected areas such as Australian Marine Parks. AMFA does not actively monitor non-Commonwealth fishing activities but follows up on reported vessels.

The CSIRO together with several partners have developed a risk report tool that allows managers to identify suspicious vessels based on a set of indicators and statistics (https://research.csiro.au/iuu/). Vessels are assigned a risk score and an alert is sent to relevant authorities when suspicious vessels enter areas that are targeted for surveillance (CSIRO, 2017). The algorithms developed for the tool are based on Global Fishing Watch, a free-online tool that allows the public to track commercial fishing vessels on a global map based on a model that uses AIS signals and fishing-related data (globalfishingwatch.org).

In addition, the team is creating algorithms for several freely-available or low-cost satellite data (e.g. Sentinel 1 and VIIRS) to detect and identify non-transmitting or “dark” vessels automatically (CSIRO, 2018).

3.3 Oil Spills

David Blondeau-Patissier (CSIRO)

3.3.1 Detecting oil spills using ESA’s Sentinel-1 SAR sensor

Marine pollution from illegal discharges or ship (or oil well /platform) accidents causes devastating short- and long-term effects, including site contamination and physical damage to the environment. This has been shown by many past events worldwide, the most known being the Deep Water Horizon oil spill accident in the Gulf of Mexico in August 2010. At the scale of Australia, the Australian Maritime Safety Authority (AMSA) registers ~7,000 incidents a year, of which only 10% are investigated. A particularly sensitive region is the Great Barrier Reef (GBR), used as a pilot region for this study. Recognized as a high-risk area for oil spills by AMSA, the heavy fuel oil (HFO) pollution that resulted from the oil pollution incidents that occurred in 2009 and 2010 had devastating consequences for the GBR. Even more insidious are illegal discharges from ships and drilling platforms because not officially reported unless detected, and the GBR is no exempt to such incidents: in July 2015, a series of illegal discharges contaminated the shores south of Townsville (Cape Upstart). Illegal oil discharges are not currently monitored routinely in the GBR and may be more frequent than anticipated.

The need of remote sensing-based oil spill monitoring systems in Australia was dramatically illustrated in August 2009 by the Montara oil spill incident in the Timor Sea. An estimated 30,000 tonnes of heavy fuel oil (HFO), aka crude oil, leaked from the Montara wellhead platform, ~250 km off the Western Australian coast, during 75 days between the 21st August and the 03rd November 2009. The monitoring of this incident did not benefit from remote sensing support, due to the lack of maturity of government capabilities at the time. Historically, such maritime incidents are best detected, and monitored, using satellite imagery from synthetic aperture radar sensors (SAR) (Solberg et al., 1999; Espedal and Johannessen, 2000; Brekke and Solberg, 2005). With oil spills illegal discharges often occurring at night and ship accidents frequently resulting from stormy weather, SAR sensors are well suited for detecting such incidents because they are active satellite instruments that operate day and/or night and in any weather, with wide swaths (> 100 Km) that can cover large areas of the ocean.

Oil spill signatures typically appears as a dark patch in a SAR image due to the decreased radar backscatter in comparison to the much brighter surrounding clear seawater (Figure 10a). The capability of a SAR sensor to detect marine oil slicks however, also depends on a multitude of parameters, including the wind speed, the SAR sensor’s properties such as its polarization, the signal-to-noise ratio, the incidence angle between the satellite sensor and the targeted sea surface, as well as the oil properties – a surface slick of vegetal oil will have a much lighter signature when compared to a slick made of HFO (Skrunes et al., 2012). Other features also appear as dark patches in SAR imagery, including but not limited to, grease, natural biogenic slicks, upwelling, rain cells, low wind speed and wind shadows from land-sheltering and current shear zones (Figure 10b). These non-oil features are termed as “look-alikes” and the difficulty resides in distinguishing true oil from false-positive signatures (Espedal, 1999; Xu et al., 2014).

Since November 2015, Australia has an official access right to the European Space Agency’s Copernicus satellite programme datasets, thanks to a cooperation agreement between the European commission and the Australian Government. A direct outcome of this agreement is the establishment of a Copernicus Sentinel regional Data Hub for Australia in March 2016, hosted by Geoscience Australia alongside CSIRO, the National Computational Infrastructure (NCI) facility and state and territory governments, to support the Australia-wide distribution and analysis of the satellite imagery acquired by the Sentinels. For this case study, the SAR sensor onboard Sentinel-1A is used. Sentinel-1A was launched on 3rd April 2014. The Sentinel-1 satellite is orbiting Earth every 98.6 minutes in a near-Earth polar orbit at 693 km altitude, and at a velocity of more than 7 km/sec. With a nominal 175 orbits in 12 days, the maximum acquisition time per day is 365 minutes. Level-1 Ground Range Detected (GRD) imagery acquired in Interferometric Wide (IW) swath mode by Sentinel-1 is the most frequent mode of acquisition over Australia. The IW mode allows for the combination of a large swath (i.e., 250 km) with a high spatial resolution (20 m resolution, 10 m pixel spacing) and a moderate incidence angle (30.42° - 45.94°), suitable for oil spill detection. In comparison, the Advanced Synthetic Aperture Radar (ASAR) from the Envisat mission (2002-2012) had a spatial resolution of 30 m. This improvement in spatial resolution is also matched by a more frequent repeat cycle by Sentinel-1 SAR, from a 35-day revisit time for ASAR down to every 12 days (over Australia) for Sentinel-1.

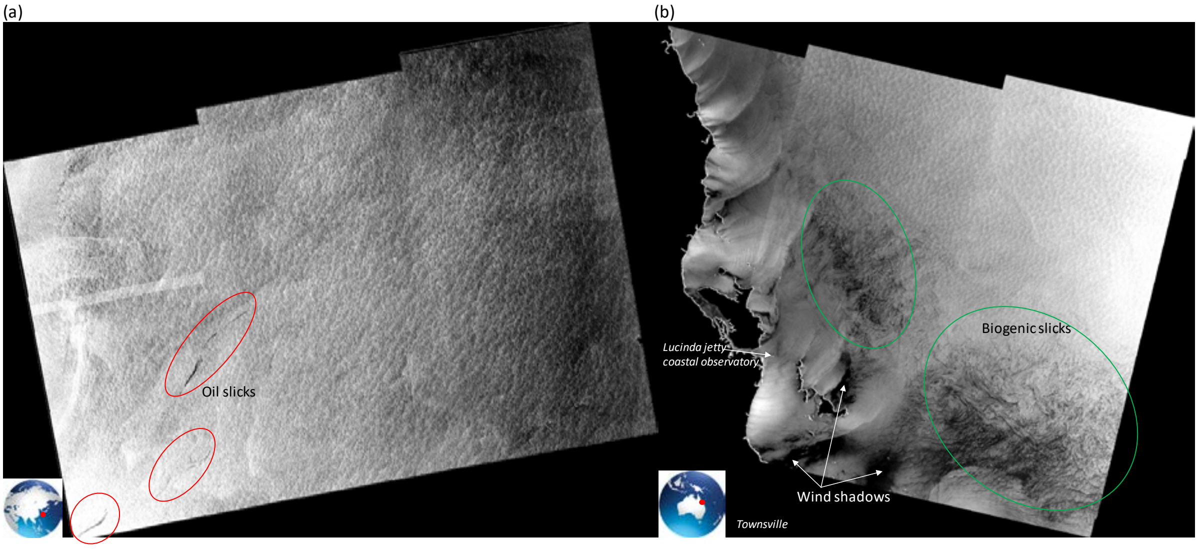


Figure 10 - (a) An oil slick seen in a Sentinel-1 SAR scene of the 20thJanuary 2018 from the Sanchi incident, China Sea and (b) biogenic slicks and wind shadows seen in a Sentinel-1 SAR scene of the 4th September 2019 acquired over the Lucinda Jetty coastal observatory, central Great Barrier Reef.

For marine applications, including in the context of oil spill detection and monitoring, single-polarimetric SAR imagery is mostly used because single polarisation images are characterized by higher radiometric resolution. Following an extensive analysis of the 5,312 Sentinel-1 SAR acquisitions over the GBR between October 2014 and August 2019, we identified two scenes in which we are confident oil slick features are present:

3.3.2 Great Barrier Reef - Fresh oil discharge off Cape York

On Wednesday 7th November 2018, Sentinel-1 SAR acquired two scenes over the Great Barrier Reef, specifically over Cape York, at 18:53 local time (AEST). The processing and analysis of one of the scenes revealed a likely 9 km-long illegal oil discharge south-east of Turtle Head Island (Figure 11). A ship, identified as a bright, white spot on this SAR image due to the backscatter reflection on the metallic target, is seen travelling 4 km south ahead of the spill (see inset of Figure 11). The clustered shape of this particular spill differs from “typical” linear oil slicks often seen in most oil spill cases (e.g. Figure 10a). This may increase the difficulty of its identification. This event is likely to be a fresh (recent) oil discharge because of the lack of feathering on the oil feature itself, compounded by the presence of the ship also seen in the image. Sunset was at 18:11 on that day, thus inferring that this event occurred at dusk and no coincident optical or thermal imagery could be acquired as a result to confirm this incident.

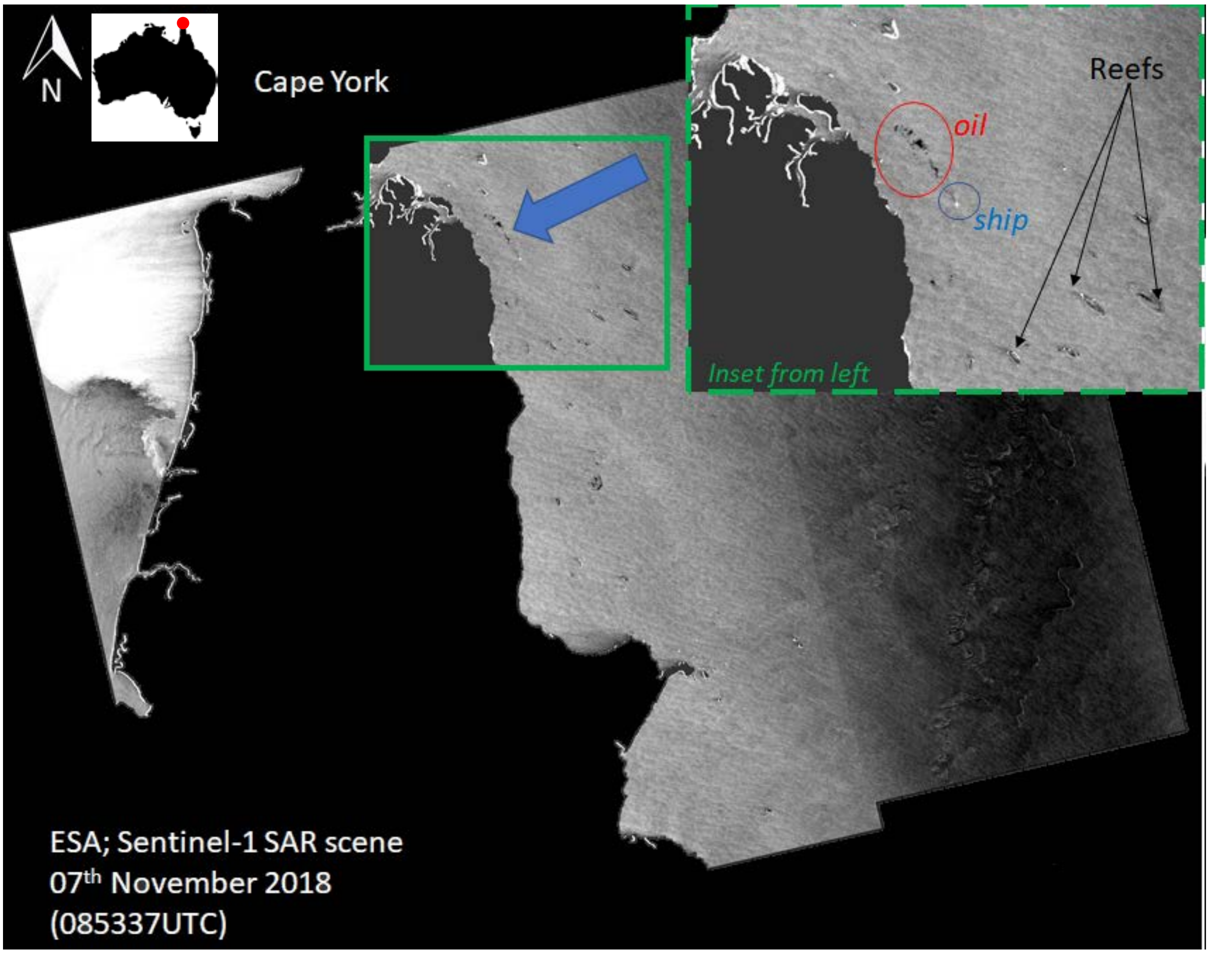


Figure 11 - Sentinel-1 SAR scene acquired on the 07th November 2018 featuring a likely illegal discharge off Cape York. The oil spill is circled in red in the inset.

3.3.3 Great Barrier Reef - Possible oil slicks off the Lucinda Jetty coastal observatory

The second scene was acquired on the 07th January 2019 at 05:44am AEST in the central GBR. Three likely oil slicks of up to 10 km in length are seen floating north east of the Lucinda Jetty coastal observatory, between the reef matrix and the shoreline (Figure 12). The SAR scene also contains wind shadows and biogenic slicks further south of this likely illegal discharge. Unlike the previous incident off Cape York however, the oil features present in the scene show some feathering, indicating that the oil slicks are not made of fresh oil and may have be subjected to weathering. Sunrise was at 04:59 am AEST on that day, thus allowing optical imaging acquisitions by other satellite sensors, such as Sentinel-3 Ocean and Land Colour Instrument (OLCI) (Figure 13). A Sentinel-3 OLCI scene was acquired over the region of interest four hours following the SAR acquisition, at 09:49 am AEST, thus allowing a direct comparison between the two scenes. The synergistic use of spatially and temporally coincident imagery from multiple satellite sensors providing thermal, optical and/or SAR information is not new (e.g., (Pohl and Genderen, 1998)), but the Sentinels missions allow to do so routinely because of the higher frequency of consistent imaging from Sentinel-1 SAR, Sentinel-2 MSI and Sentinel-3 OLCI. In the context of oil spills, using optical information in conjunction with SAR may increase the assessment accuracy of potential oil spills detected in Sentinel-1 SAR scenes. This is particularly effective when Sentinel-2 MSI imagery is available, because the 10-20 m spatial resolution allows for a direct comparison to Sentinel-1 SAR 20 m spatial resolution. With this Sentinel-3 OLCI scene however, the resolution was down to 300 m, more than 15 times lower than the SAR acquisition. Near-infrared bands can be used to better detect surface oil slick features and OLCI's band at 865nm was used to that effect (Figure 13a). A clear boundary between water masses extending up to 15 km offshore can be seen in the optical image (Figure 13a-b). It is possible that the oil slick features in the Sentinel-1 SAR imagery are biogenic surfactants, but it is surprising that the remaining of the water mass boundaries are not seen in the SAR scene. Thus, it remains possible that the candidate features identified in the Sentinel-1 SAR are oil slick features.

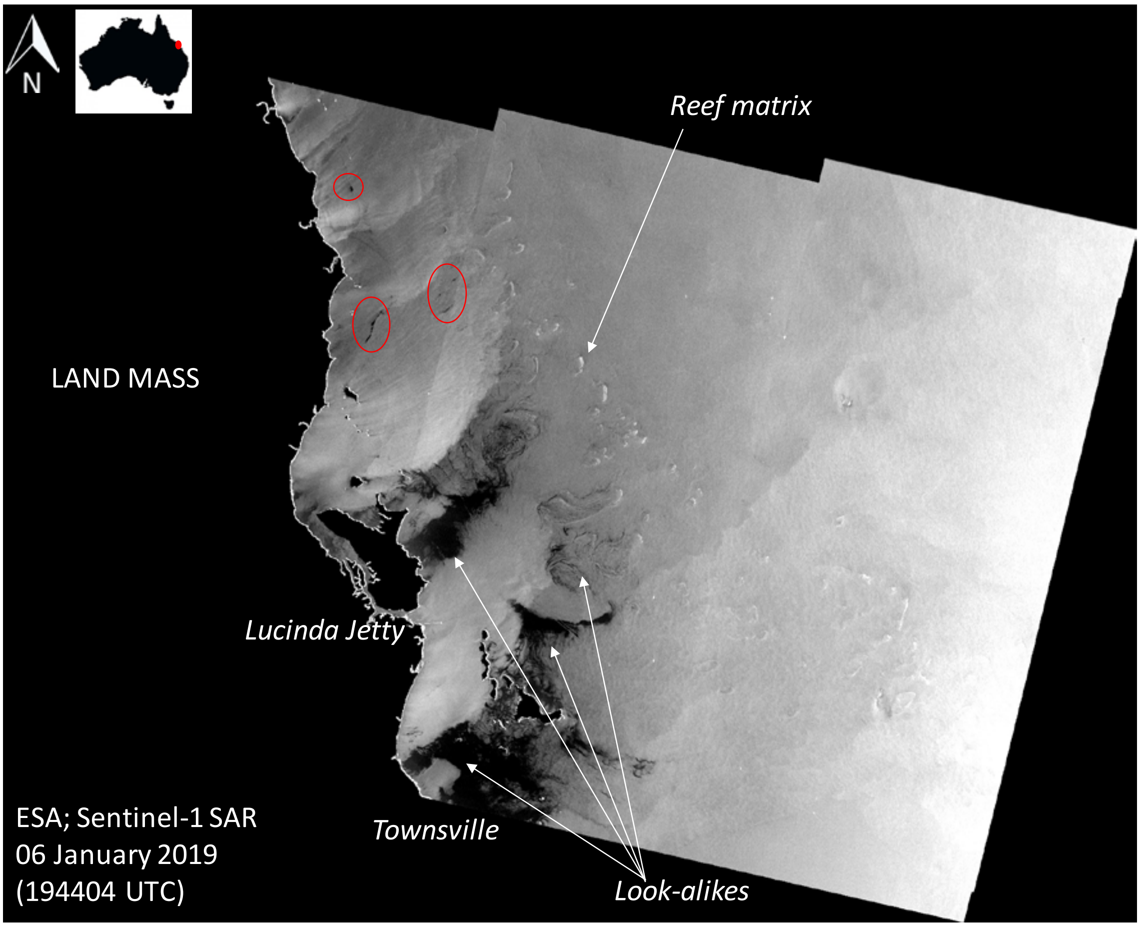
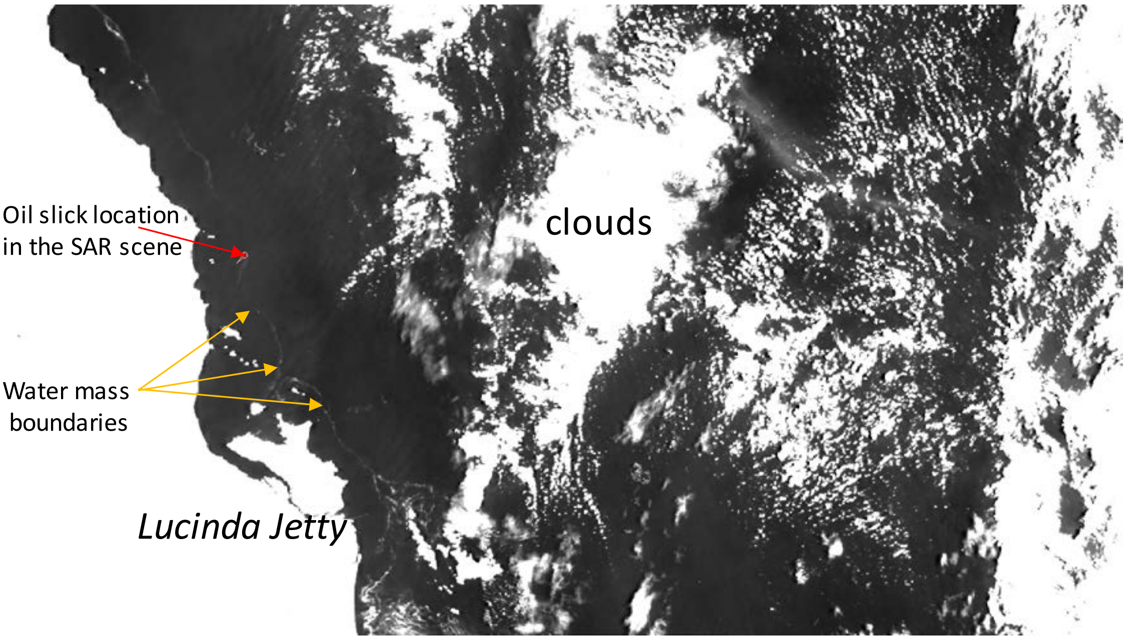
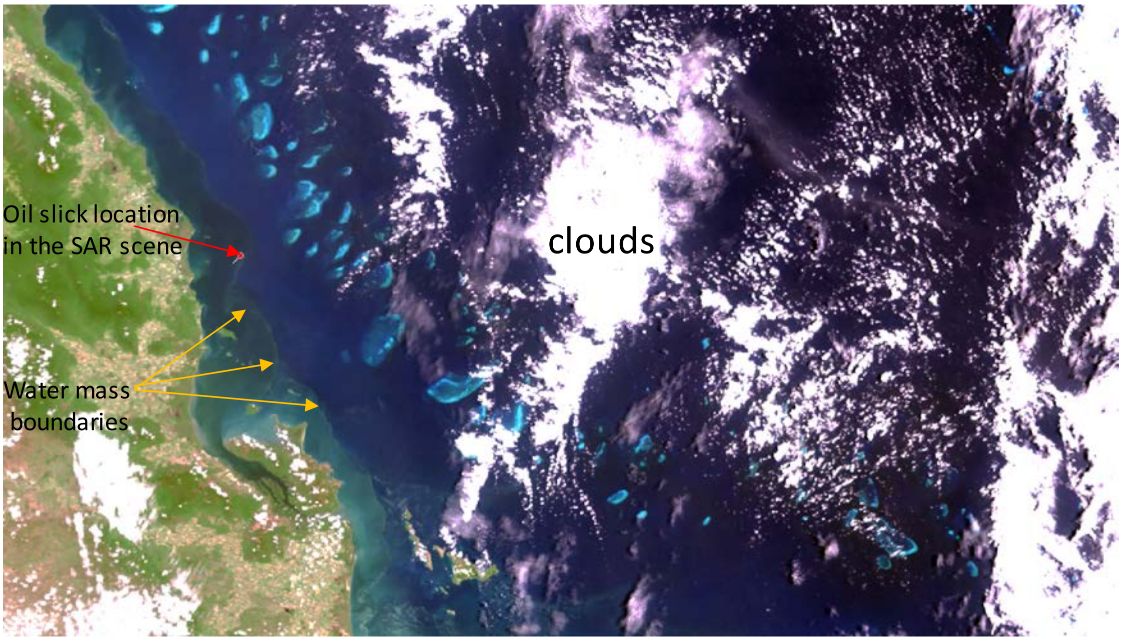


Figure 12 - Sentinel-1 SAR scene acquired on the 6th January 2019 (05:44am AEST) featuring oil slick features off the Lucinda Jetty. The oil slicks are circled in red.



(a) Sentinel-3 OLCI, 865 nm (Top of the atmosphere radiance band 17)



(b) Sentinel-3 OLCI, true-colour composite (band stretched)

Figure 13 - Sentinel-3 OLCI scene acquired on the 6th January 2019 (09:49am AEST), 4 hours following the SAR acquisition. (a) Near-infrared band at 865 nm; (b) true-colour composite with band stretching to further highlight the various coastal features. The position of a possible oil slick, the longest of the three, is indicted by a red pin.

3.4 Marine Debris

Inke Falkner (GA)

3.4.1 Capabilities and platforms

Marine plastic pollution is widespread, persistent and its ecological impacts varied (Rochman et al., 2016). Although estimates of the amounts of plastic entering the world's oceans have been published (Sebille et al., 2012; Eriksen et al., 2014; Jambeck et al., 2015), there are still uncertainties about the sources, sinks and routes of marine plastic litter (Reisser et al., 2013). Satellite remote sensing offers an opportunity to monitor the fraction of large marine plastic litter that is floating on the surface on a broad spatial scale, but this application is still in its early stages. To date only a handful of studies have explored potential applications for satellite and airborne remote sensing to assess ocean plastic pollution (Garaba et al., 2018; Garaba and Dierssen, 2018).

Optical remote sensing can be used to detect large marine debris or large congolmerates of debris. Progress has been made in hyperspectral remote sensing of marine macroplastics in the visible (400-780nm) and short-wave infrared (1.1-3 μm) spectrum. While infrared energy only penetrates a few millimetres into the water column and is therefore limited to surface detection, subsurface detection can be achieved using the visible spectrum (Mace, 2012). Garaba and Dierssen, (2018) have used airborne RGB and hyperspectral shortwave infrared imagery to detect ocean plastics in-situ and identified a number of unique spectral features common to plastics in the short-wave infrared spectrum.

Goddijn-Murphy et al., (2018) have developed a reflectance model based on geometrical optics and the spectral signatures of one type of plastic and seawater using the visible and short-wave infrared. The model can be used to select optimal wavelengths and develop a working algorithm for satellite remote sensing of marine macroplastics. And it takes the colour, transparency, reflectivity and shape of the plastic litter into account. However, currently the model has a number of limitations; only one type of plastic with certain optical properties and a specific shape has been incorporated, whereas macroplastic debris in the ocean is made up of many different shapes and chemicals. Version 2 of the model aims to include a mix of plastic litter types and shapes to reflect conditions more accurately. Different polymers seem to have characteristic spectral signatures, but the colour of the plastic also seems to change the spectral signature, which complicates matters.

We also need to consider the atmospheric correction methods that are used when processing the data. Most correction methods will mask the signals from plastic on the ocean surface and uncorrected data is needed to apply alternative correction algorithms. Surface waves additionally mask plastic signals and it is recommended to only use satellite data under low wind speed conditions (less than 3 or 4 ms^{-1}) (Goddijn-Murphy et al., 2011).

Finally, biological fouling of plastic pieces floating in the ocean changes their optical properties with algae absorbing wavelengths in the visible spectrum. Any algorithm developed to detect marine debris should therefore include wavelengths in the infrared rather than the visible spectrum, which will limit the water depth plastic debris can be detected in.

3.4.2 Application in MPA monitoring

The routine detection of floating plastic debris using existing satellite remote sensing missions is technically not feasible yet. But satellite sensors relevant for different aspects of marine debris observations can potentially be adjusted and algorithms are being developed.

Most importantly, sensors will need to be calibrated using comprehensive in-situ data for different types of marine debris as stated in Goddijn-Murphy et al. (2018). Producing these in-situ datasets will take some time. In the absence of readily available remote sensing products, that can directly measure the presence or absence of marine debris, using indirect measurements of environmental characteristics to identify areas where debris items are more likely to accumulate may be a useful approach. Identified areas can then be targeted in future surveys and/or at higher-resolution e.g. with airborne measurements.

To follow the pathways of floating debris requires the measurements of surface currents and winds, which are currently derived from remotely-sensed altimetry and scatterometry data and validated with in-situ measurements from the global drifter array. Being able to observe the motion of marine debris would not only provide a wealth of information to validate surface currents it could also outline main pathways of different types of pollution and potentially track their source. In Australia debris washing up on remote reef beaches could possibly be detected using high resolution spatial data as some of the exposed reefs capture large amounts of debris (Dekker, pers comms) (Figure 14). Satellite remote sensing can and most certainly will make a valuable contribution in the monitoring of marine plastic debris in the future

Figure 14 - Debris collected at Lihou Reef, Coral Sea Marine Park (photo © Arnold Dekker).

3.5 Fisheries stock assessments

Inke Falkner (GA)

3.5.1 Capabilities and platforms

Over the past decade, there has been a global shift towards an ecosystem-based approach to fisheries management, recognizing the complexity of ecosystems and the interconnections among their component parts. Such an approach requires an understanding of the biological and environmental characteristics that define ecosystems.

The importance of sea surface temperature for fisheries management is mainly due to its usefulness as an indirect indicator of areas abundant in fish food i.e. plankton and nekton organisms, which attract fish aggregations (refer to ‘Linking the physical and biological environment’ section). Thermal fronts in particular seem to be associated with high concentrations of food for fish (Klemas, 2013). Increased phytoplankton biomass due to monsoonal upwelling strongly influenced sardine abundance in the south-eastern Arabian Sea (Smitha et al., 2019). Similarly, upwelling measured using SST and Chl-a data on the west coast of India is linked to higher herbivorous fish yields in the region (Rajkumar and Shanmugam, 2018). Ocean colour, the measurement of primary production from space, has thus filled an important knowledge gap as it provides the only means of quantifying the base of the pelagic food chain on a global scale (Platt et al., 2008; Platt and Sathyendranath, 2008).

Fisheries stock assessments have often included satellite data in combination with tagging or catch data in order to understand the environmental variables that drive the distribution of the exploited species (Enever et al., 2017; Harrison et al., 2017). In the open ocean mesoscale structures such as fronts, eddies, and filaments are important ecosystem features, often associated with enhanced productivity and fish aggregations (Klemas 2013). In this context, the availability of global, daily, systematic, high-resolution images obtained from satellites has been a major data source for elucidating the relationships between exploited marine organisms and their habitat (Polovina and Howell, 2005). Habitat maps are being used either to restrict fishing grounds or to prompt fishers to move towards favourable areas.

In Australia, Hobday et al., (2010; 2011) identified several dynamic pelagic habitats in oceanic waters off southern and eastern Australia to predict the abundance of several high trophic level fish species including bluefin and yellowfin tuna using a number of satellite-derived datasets. This body of work culminated in forecast products that now assist in the sustainable management of these species in Australia and represent two of the first of such forecast products now available (Eveson et al., 2015; Alistair J. Hobday et al., 2016; Payne et al., 2017). Nevertheless, it is important to keep in mind that using these proxies does not tell us where target species are, but where they could potentially be based on habitat preferences and ecological niches (Payne et al. 2017).

The key to understanding the variability of fish populations lies in understanding the ecological drivers that strongly affect the early life history stages in the plankton with food variability strongly affecting the success of a cohort (Chassot et al., 2011; Klemas, 2013; Payne et al., 2017). Satellite visible and NIR spectral radiometry (ocean colour) have previously been used to measure the abundance and variability of food at critical periods during larval development (Platt et al., 2003), but this has yet to be applied more broadly to recruitment predictions. In this context, the construction of long-term satellite data time series of phytoplankton biomass and composition in combination with other measurements such as SST, sea surface height and wind allows us to analyze the effects of ecosystem fluctuations on the recruitment of exploited stocks.

Other ecosystem metrics that may be relevant to fisheries applications that can be derived from satellite data are phytoplankton community composition e.g. the presence of diatoms and size structure (Sathyendranath et al., 2004; Loisel et al., 2006; Forget et al., 2011; Jackson et al., 2011). Phytoplankton community structure may have profound effects on the trophic links in the rest of the food chain. For example, Lingen et al., (2006) and Cury *et al.* (2008) established that, in the Benguela Current system, food environments dominated by small cells (e.g. flagellates) favour a sardine (*S. sagax*) fishery, whereas food environments comprising large particles (e.g. diatoms) favour an anchovy (*Engraulis encrasicolus*) fishery. Such changes are probably related to the size of the phytoplankton cells, as well as their taxonomic status, so that the retrieval of phytoplankton size structure from remote sensing is equally important. Whether or not these research products can be developed into robust indicators in a monitoring program remains to be established.

3.5.2 Application in MPA monitoring

Forecasting products developed and used for sustainable fisheries management could be highly relevant in the context of marine conservation management. Statistical forecasts of the physical environment e.g. sea surface temperature anomalies and climate models predicting the variability of large-scale climatic and oceanographic patterns that influence biological processes that are of interest to both fisheries and conservation managers. Ecological forecast systems, so-called “if-then” forecasts that include a list of ecosystem responses can be a valuable first step. However, forecasting products that incorporate biological and physical models are most valuable (Payne et al. 2017). In this context Payne et al. (2017) made the following observations:

- Physics-based models are preferable to empirically derived models.
- Development of biological forecast products should focus on physical variables that can be reliably predicted on different spatial and temporal scales
- There should be a focus on tight cause-and-effect relationships i.e. selection for the most direct biological response to respective physical driver.

Most importantly, the end-user should be involved in the development of the forecasting product from the planning through to the application stage and subsequent evaluation to make sure the product is used and has the intended benefits (Hobday et al., 2016; Payne et al., 2017). Stakeholder input to develop specific monitoring questions is therefore needed before we are able to develop research tools into robust monitoring indicators for particular use cases.

4. FUTURE TRENDS AND ISSUES

Stephen Sagar (GA)

4.1.1 Next generation sensors

In Section 2.3 we discussed the concept of tradeoffs between sensor characteristics such as spectral resolution, revisit time, spatial resolution and coverage. While this is still very much the case, technological advances mean that boundaries are quickly breaking down across these traditional sensor definitions, and in this section we look at two of these examples.

In the ocean colour space, the Plankton, Aerosol, Cloud, Ocean Ecosystem (PACE) mission is a next-generation satellite due for launch by NASA in late 2022 to early 2023. The PACE mission includes three instruments, one hyperspectral ocean colour imager and two multi angle polarimeters, which together will provide more information than heritage ocean colour systems to better understand not only ocean colour, but also a range of atmospheric parameters (Werdell et al., 2019).

The Ocean Colour Instrument (OCI) onboard PACE has been built based on lessons learnt from heritage missions such as MODIS, SeaWIFS and VIIRS. With a full hyperspectral resolution, coupled with a 1km resolution and 1-2 day revisit period, it will be capable of answering more complex questions around issues such phytoplankton composition and absorbing aerosols, than any other previous ocean colour mission (Figure 15).

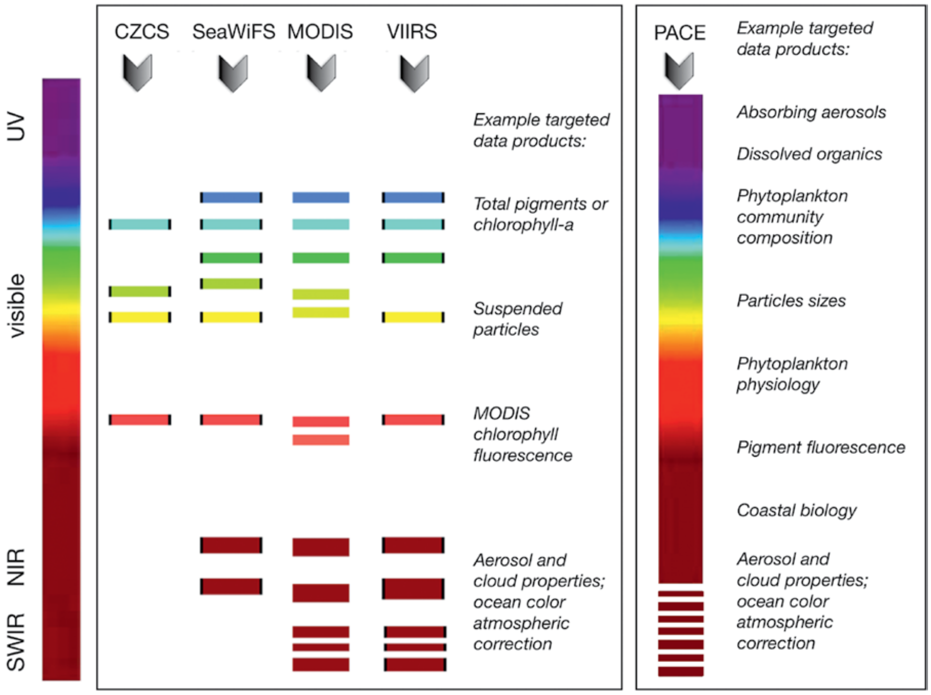


Figure 15 - Spectral capabilities of several heritage satellite radiometers in comparison with PACE, highlighting examples of associated data products that can be retrieved with such capabilities (Werdell et al. 2019)

In the coastal and shallow water space, one of the more significant recent developments is the maturation of Cubesat constellations suitable for application to aquatic applications. Cubesat constellations consist of multiple small satellites, often with simple multi-spectral capabilities, deployed in large numbers to enable both high revisit times and high spatial resolution. The most advanced Cubesat constellation are the PlanetScope Dove satellites, consisting of over 120 satellites with 4-band multispectral sensors able to image the entire globe daily at resolution of 3.7m (PLANET, 2019).

The potential of this blending of high resolution and high revisit time and coverage has been already demonstrated by the integration of the PlanetScope data into the Allen Coral Atlas project (https://allencoralatlas.org/), which has the ambitious aim of mapping the world's coral reefs by 2020. As part of this project, researchers have demonstrated that the Planet data is of sufficient quality (radiometric, atmospheric correction) to enable algorithms to be designed for shallow water bathymetry estimation (Li et al., 2019). By combining these methods with the integrated mapping approach of Roelfsema et al., (2018), there is great potential for Cubesat data to underpin high resolution global mapping aims such as that of the Coral atlas project. It should be noted however that these data are from a commercial provider, and as noted in earlier sections, their associated cost likely prohibits their use as a monitoring tool at this point in time.

4.1.2 Computational Infrastructure and Analytics

The dual drivers of technological advances in computational infrastructure and the public release of archives of earth observation data has led to a new generation of platforms designed to leverage opportunities these vast collections of data can provide. The core principle of these platforms is around the concept of "build once, use many", by providing data storage, access and analytics in the same location.

The most high profile example of this in a cloud environment is Google Earth Engine (GEE). GEE provides access to a range of publicly available earth observation and environmental data sets via an Internet-accessible application programming interface (API) and an associated web-based interactive development environment (IDE) (Gorelick et al., 2017). Users can sign up to the platform and receive a quota for both uploading personal data and saving intermediate products and analysis.

In Australia, data cube infrastructure was pioneered through the Australian Geoscience Data Cube (AGDC) project (Lewis et al., 2017) which has since matured into the Open Data Cube initiative, of which Digital Earth Australia (DEA) is the Australian government implementation (Dhu et al., 2017). DEA is an analysis platform and archive for satellite imagery, hosted by Geoscience Australia and is unique for Australia in that it offers both a fully searchable catalogue of analysis-ready data (ARD) whilst also enabling detailed on-the-fly investigation and analyses (Lewis et al. 2017). The ARD mean that these data are pre-processed and corrected for Australian conditions, including a rigorous geospatial and atmospheric correction, to enable time-series and pixel based processing across sensors going back over 30 years for the full continent.

One of the strengths of the DEA is its capability to provide a framework to value add to data products already being produced by other government providers. For example, ocean data products developed by IMOS and ESA can be ingested into the DEA to enable repeat analyses and interpretation. The ability to establish a time series of data that can be stored and queried on a computational infrastructure removes the barriers of computational power, storage and data download when considering ocean scale analyses over time. Such analyses can provide essential baseline information on variables including ocean colour, which have the potential to contribute to ongoing monitoring and management practices for off-shore regions like Australia's Marine Parks.

Utilising both the National Computational Infrastructure (NCI) and Amazon Web Services (AWS), DEA provides a wide range of analytic tools and mechanisms for users to access the data, develop their own code and analysis, and integrate outputs into their own workflows. These tools range from Python API's to enable users to leverage the full computational power of the NCI for continental scale applications, through to web browser based Jupyter notebooks which enable less code savvy users to access pre-built tools and generate science products from the DEA archive on AWS.

ODC implementations such as the DEA provide great flexibility to integrate Earth Observation data across types and scales, including elevation, bathymetry, ocean colour sensor data, SAR data and more. These data can also be processed with regional considerations in mind, to create ARD specific to the region of the data cube. This is an important consideration in marine and aquatic applications, where as we discuss in the following section, atmospheric correction is so crucial.

4.1.3 Analysis Ready Data in Coastal and Complex Waters

One of the key components of ARD is atmospheric correction, or the removal of atmospheric effects from the radiance received at the sensor. Effective atmospheric correction is essential to ensure surface reflectance products across time steps and sensors can be compared and analysed, so that physics based algorithms can be employed on a sound theoretical basis. In aquatic based applications, atmospheric correction is even more important, as compared to land surfaces, water-leaving radiance is only a small proportion of radiance received back to the sensor; thus the confounding influence of the atmosphere plays a much bigger role.

Many atmospheric correction methods developed for open oceans and for ocean colour data require significant adaptation for use with higher resolution multispectral sensors (e.g. Franz et al., 2015). In coastal waters with more complex water types, variations in aerosol types and adjacency effects from nearby terrestrial influences, alternative approaches for atmospheric correction must be used, particularly for higher resolution sensors such as Sentinel-2 and Landsat OLI.

There are a wide variety of methods used for coastal, complex and inland water atmospheric correction, and the problem is an ongoing and active area of research (Steinmetz et al., 2011; Vanhellemont and Ruddick, 2015; Brockmann et al., 2016; Pahlevan et al., 2017; Keukelaere et al., 2018; Vanhellemont, 2019). In most evaluations of these range of methods, different models are shown to perform better or worse across varying scenarios, and there is no clear consensus on the ‘best’ methods across all situations (Ansper and Alikas, 2019; Warren et al., 2019). There are active initiatives to formalize this kind of evaluation in a collaborative manner, such as the Atmospheric Correction Inter-Comparison Exercise (Doxani et al., 2018) which has now been extended to coastal and inland waters in phase 2 of the study to help inform users of the various strengths and weaknesses of each approach for higher resolution data.

Within DEA, development of a radiative transfer atmospheric correction method that aligns with the processing chain of the terrestrial Landsat and Sentinel 2 ARD data is underway. This method incorporates corrections for adjacency and sky-glint, whilst sourcing aerosol information from ancillary modelling. Initial results have shown this to be a promising solution to operational atmospheric correction of coastal data, however further validation and testing is still in progress.

Another approach for ocean colour data utilised within Australia is the artificial neural network (ANN) method of Schroeder et al., (2007) originally developed for MERIS and implemented operationally for MODIS data within the eReefs project (see section 2.3.2). Tuned regionally, this method is a coupled inversion of both the water and atmospheric components, and has the added benefit of providing aerosol products that can potentially feed into other ARD and product workflows.

4.1.4 Integrated modelling and forecasting approaches

One of the most promising areas in which earth observation in marine regions can contribute is through its integration into various modelling and forecasting applications. Data assimilation methods utilizing EO data to guide simulations and help provide better model estimates are becoming increasingly prevalent in marine ecosystem modelling (see Groom et al., (2019) for a summary), whilst EO data is also finding a role in helping to spatially link forecasting based on climate models in marine ecological models (Payne et al., 2017). Below we briefly introduce two applications in Australia based on the integration of modelling and EO data; more information on these projects can be found in the associated references.

EREEFS

eReefs is a interoperable information platform developed for the Great Barrier Reef (GBR) region to provide users with improved environmental information to assess past, present, and future conditions, as well as management options to mitigate the risks associated with multiple and sometimes competing uses of the GBR. The platform and project is built upon an integrated system of data, catchment and marine models, visualisation, reporting and decision support tools that span the entire GBR area (Steven et al., 2019).

The eReefs suite of marine models include hydrodynamic, biogeochemical and sediment transport models regionally tuned for the GBR (Baird et al., 2019). As part of the data assimilation component of the platform, the earth observation ocean colour products and processes that have been introduced in earlier sections of this report are incorporated to support these marine models through comparison to simulated and observed water leaving radiances (Baird et al., 2016b; Jones et al., 2016).

The assimilated platform enables hindcasting, nowcasting and forecasting of all relevant variables in the entire GBR at 1km and 4km domain scales and is underpinned by an extensive in-situ monitoring network for both validation and further data assimilation (Figure 16). Demonstrations of the types of model outputs and applications relevant to MPA monitoring include seagrass growth (Baird et al., 2016a), coral reef health and bleaching response (Gustafsson et al., 2014; Baird et al., 2018), chlorophyll synthesis (Baird et al., 2013), and production by the marine cyanobacteria Trichodesmium (Robson et al., 2013).

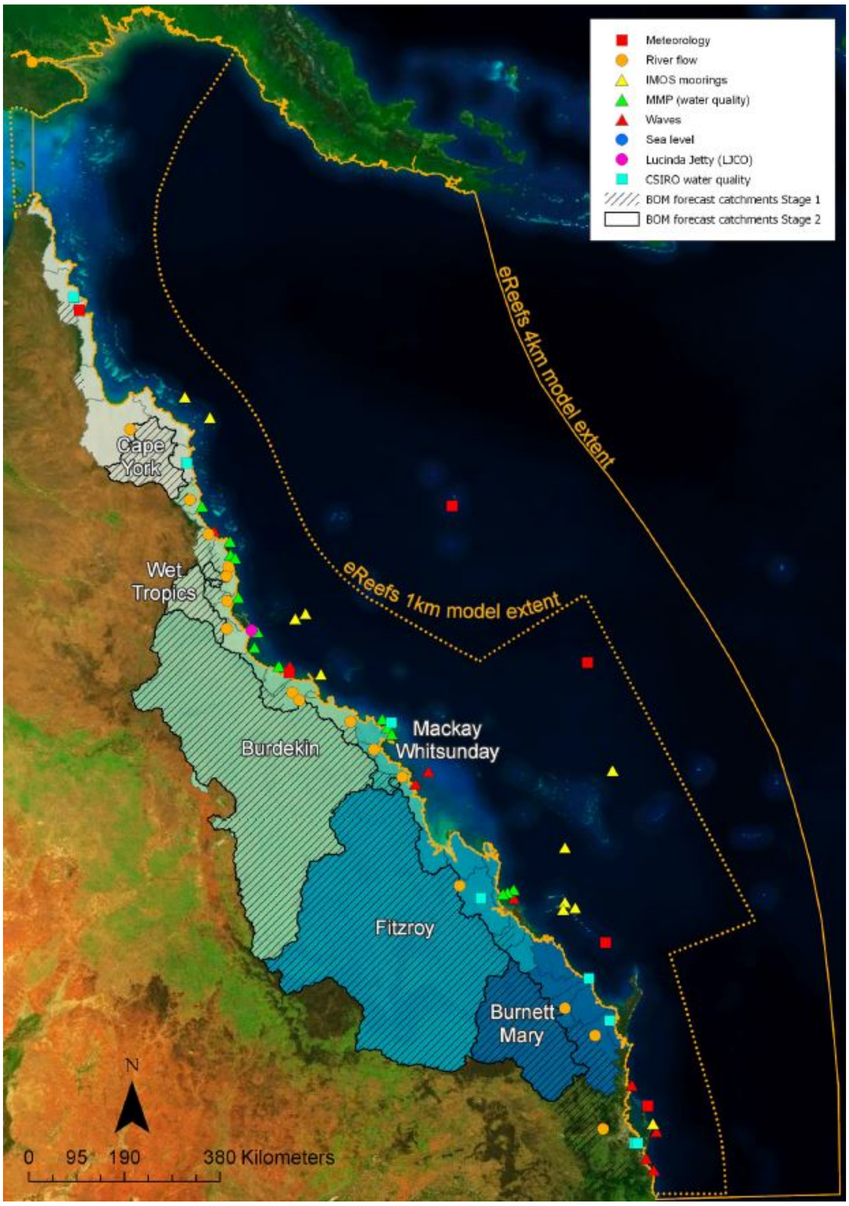


Figure 16 - The extent of the eReefs modelling domain across the GBR, including in-situ monitoring locations (Steven et al. 2019).

TIDAL MODELLING AND COASTAL APPLICATIONS

The DEA platform provides not only an environment to analyse different sensor data, but also to easily integrate models with time series analysis workflows and continental scale archives of EO data. In the coastal zone, integration of the Oregon State University developed tidal prediction software (OTPS) (Egbert and Erofeeva, 2002, 2010) has enabled a range of products with potential monitoring applications in coastal MPAs.

The National Intertidal Digital Elevation Model (NIDEM) was developed based on the original Intertidal Extents Model (ITEM), and is the first continental scale elevation model produced for Australia's intertidal zone, the area exposed between high and low tide (Sagar et al., 2017; Bishop-Taylor et al., 2019). The intertidal region is highly diverse and crucial ecosystem for migratory shorebirds, however it is notoriously difficult to map and survey, and thus is poorly understood at a national scale.

NIDEM is based on a tidal tagging of the 30 year archive of Landsat data in the DEA using the OTPS model, which assigns a tidal height to each observation based on time of acquisition. A sorting and median filtering process then enables contours to be extracted, and a DEM produced that is comparable to LIDAR validation data across most environments (Bishop-Taylor et al., 2019) (Figure 17).

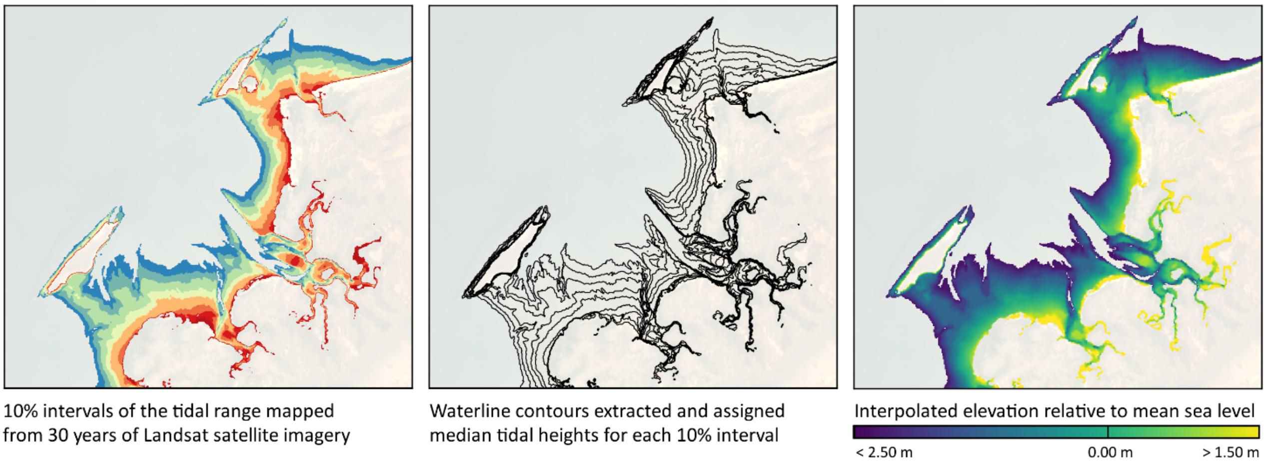


Figure 17 - The National Intertidal Digital Elevation Model (NIDEM) process showing contour extraction and DEM interpolation based on a tidally sorted 30 year archive of Landsat imagery (Bishop-Taylor et al. 2019)

Recent work has shown the potential of using Landsat and Sentinel-2 data to extract shoreline positions and change at a resolution far greater than the 10-30m of the original source data (Vos et al., 2019). This concept is further explored in DEA by constraining the shoreline analysis technique by tide, to isolate shoreline change detection through time (Figure 18) and evaluate the sensitivity of the process to various water index selections.

Figure 18 - Coastline change over the last 30 years in North Coogee, Perth, WA based on the Landsat archive in DEA. This location was identified as one of 55 coastal erosion hotspots in a recent WA government report linked below. Left – Yearly high tide shoreline from 1988 (yellow) to 2018 (red) Right – Calculated rate of erosion (red) or accretion (blue) per year. (https://www.transport.wa.gov.au/mediaFiles/marine/MAC_P_CoastalErosionHotspotsAppendixD135-191.pdf)

This kind of shoreline change and detection process has the potential to be applied at remote atolls across MPA's; difficult to survey using physical techniques. By correlating this analysis with drivers from a range of climate variables, the project is looking to explore the potential of including a forecasting ability within the modelling process.

5. SUMMARY

Stephen Sagar (GA) and Inke Falkner (GA)

There is a recognised potential for Earth Observation (EO) products to feed into monitoring systems and protocols for environmental variables, and to do so in a standarised and repeatable manner. The long time series and spatial coverage provided by many EO sensors does mean that EO is one of the only methods of observation to provide such broad scale temporal and spatial coverage of ecosystems as vast as oceanic and coastal waters. This positions it well to address some of the components of marine park monitoring and management, ranging from the establishment of environmental baselines, through to near-real time mapping of phenomena and habitats. Despite this potential, actual uptake of EO products for marine park monitoring, management and reporting has been limited within Australia.

One of the challenges in increasing this uptake and use of EO products in marine parks is ensuring the alignment of the products with management reporting needs. As Payne et al., (2017) note when discussing marine ecological forecasting products, "moving forward will require striking a balance between what is *feasible* and what is *useful*". The key to this balance is closer communication and engagement with marine park managers, to bridge that gap between potential science and practical end use.

Products by their nature are developed from a scientific standpoint, and in this report we have given a general overview in Section 2 of some of the principles and methods used to develop some of the fundamental EO marine data products and applications. It is the translation from science product to management decision ready product that requires the closest communication and engagement with marine park managers, and often may need to happen earlier in the product development phase to ensure alignment. This extends to concepts as simple as data format. For example, the science community widely adopts formats such as NetCDF, whilst the complexity of this data format to a marine park manager may present a significant barrier to its use.

For EO data to be taken up and incorporated into standard marine monitoring programs, image processing infrastructure needs to be automated as has been done through IMOS/CSIRO facilities and Digital Earth Australia. Ideally, all data should be pre-processed, available in standardised coordinates, and accessible with a range of analysis tools available. It is envisaged that data streams from the Copernicus program and Sentinel 2 & 3 missions will be particularly useful for future applications, particularly with the provision of these corrected data sets in near real time.

Due to the versatility of EO data, it is important to develop products that target specific conservation issues and/or complement existing MPA monitoring programs in collaboration with conservation managers. More often than not, EO data is not a solution in and of itself. For instance, one of the primary considerations is that is only an indicator of near surface phenomena, often requires in situ calibration, and its real strength is as a complementary data source to assist the development of monitoring frameworks.

As earth observation moves from hindcasting and near real-time observations to forecasting, remotely sensed data are only one data stream feeding into increasingly sophisticated prediction models. In general, combining satellite observations with well-designed in-situ observations is highly desirable because the two data types complement each other well. In situ observations are able to provide fine-scale, often vertically-resolved data, whereas satellite data yield high-resolution, georeferenced horizontal maps.

Nowadays, satellite data can be processed in real-time and therefore give a valuable environmental context in which to place biological processes. In particular, anomalous events can give immediate warning in cases where ecosystems are susceptible to the strong departures from the climatological mean. The standardized repeatability of satellite observations allows the creation of detailed time-series to identify and quantify change over time, therefore potentially increasing the effectiveness of monitoring programs.

6. REFERENCES

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