Canadian Science Publishing

REVIEW



# Earth observation applications for coastal sustainability: potential and challenges for implementation[1]

Eirini Politi, Shona K. Paterson, Rory Scarrott, Eimear Tuohy, Cathal O'Mahony, and Walther C.A. Cámaro-García

**Abstract:** The coast is home to unique ecosystems, where complex ecological processes take place through the interaction of terrestrial, aquatic, atmospheric, and human landscapes. However, there are considerable knowledge and data gaps in achieving effective and future change-proof sustainable management of coastal zones around the world due to both technical and social barriers, as well as governance challenges. Currently, the role of Earth observation (EO) in addressing many of the recognised information gaps is small and under-utilised. While EO can provide much of the spatiotemporal information required for historical analysis and current status mapping, and offers the advantage of global coverage; its uptake can be limited by technical and methodological challenges associated mostly with lack of capacity and infrastructure, product accuracy and accessibility, costs, and institutional acceptance. While new initiatives and recent technological progress in the EO and information technology arena aim to tackle some of these issues so that EO products can be more easily used by non-EO experts, uptake is still limited. This paper discusses how EO can potentially inform transformative practices of planning in the coastal water zone, by using examples to demonstrate the EO potential in providing information relevant to decision-making framed by international agreements, such as the United Nations Agenda 2030, the Convention on Biological Diversity, and the Sendai Framework for Risk Reduction. By presenting evidence for how EO can contribute to innovative opportunities and data synergies at scale, the paper discusses opportunities and challenges for a more solution-led approach to sustainable coastal management.

*Key words:* Earth observation, sustainability, coastal management, international conventions, data integration.

Received 26 October 2018. Accepted 26 June 2019.

**E. Politi.** Odermatt & Brockmann GmbH, CH-8006 Zürich, Switzerland.
**S.K. Paterson.** Future Earth Coasts (FEC), University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland; Coastal and Marine Systems, Marine and Renewable Energy (MaREI) Centre, Environmental Research Institute, University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland.
**R. Scarrott.** Department of Geography, Environmental Research Institute, University College Cork, College Road, Cork, County Cork T12 YN60, Ireland; Observation and Operations, MaREI Centre, Environmental Research Institute, University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland.
**E. Tuohy and W.C.A. Cámaro-García.** Observation and Operations, MaREI Centre, Environmental Research Institute, University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland.
**C. O'Mahony.** Coastal and Marine Systems, Marine and Renewable Energy (MaREI) Centre, Environmental Research Institute, University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland; Observation and Operations, MaREI Centre, Environmental Research Institute, University College Cork, Haulbowline Road, Ringaskiddy, County Cork P43 C573, Ireland.
**Corresponding author:** Eirini Politi (e-mail: eirini.politi@odermatt-brockmann.ch).

[1]This paper is part of a Collection entitled "Crafting Options, Approaches, and Solutions Towards Sustainability (COASTS) for Coastal Regions of the World".

## Introduction

International efforts, such as aspirational global conventions including the United Nations 2030 Agenda for Sustainable Development (hereinafter 2030 Agenda), the Convention on Biological Diversity (CBD), the Sendai Framework for Disaster Risk Reduction, and the Conference of the Parties (COP21) Paris Agreement, call for progress to be made towards a more resilient and sustainable future worldwide. Delivering progress towards these conventions demands large amounts of different types of data from multiple sources. For the 2030 Agenda alone, a global indicator framework was developed by the Inter-Agency and Expert Group on Sustainable Development Goal Indicators (IAEG-SDGs) in 2017 that includes 232 indicators across 17 goals (United Nations 2018; www.un.org/sustainabledevelopment/sustainable-development-goals/). The Sendai Framework, designed to function as a management tool to help countries develop disaster risk reduction strategies, make risk-informed policy decisions, and allocate resources to prevent new disaster risks, identifies another 38 indicators for four priority areas and seven targets (UNISDR 2015; www.unisdr.org/we/monitor/indicators). The data requirements for these two conventions alone are extensive, but when coupled with more well-established conventions, such as the CBD, which itself has five goals and 20 targets (CBD 1992; www.cbd.int/sp/targets/), the magnitude of the challenge becomes clearer. This unprecedented demand for data, coupled with an unparalleled rate of innovation in data collection techniques and technologies, and the capacity to distribute data widely and freely, has expanded the horizon of possibility for solutions. The adoption of 2030 Agenda and the Sendai Framework, both in 2015, present strategic opportunities to build on the momentum of the data revolution and demonstrate the centrality of data for development (Espey et al. 2015).

The need to recognise and contribute to data collection is particularly pertinent in a coastal and ocean context, where management-relevant data have traditionally been difficult to generate (Rumson et al. 2017). More than any other geographic space, coasts are the place where the greatest confluence of societal activities occurs. With approximately 356 000 km$^2$ of global coastline (Central Intelligence Agency 2016) benefiting from the convergence of some of the most productive and dynamic natural systems, coasts provide a large range of all four categories of ecosystem services: supporting, provisioning, regulating, and cultural services (Rodriguez et al. 2005; Neumann et al. 2017). Along the coast, services such as coastal hazard protection (Spalding et al. 2014), food and livelihood security (Visbeck et al. 2014), carbon sequestration (Chmura et al. 2003), and recreation opportunities (Spalding et al. 2017) are all essential for human well-being at every scale (e.g., see Wheeler et al. 2012 for well-being benefits associated with populations living by the coast in the UK). However, much of the world's coast represents a ribbon of exposure to natural hazards with a history of catastrophic impacts. Climate warming and sea-level rise (SLR) are already negatively affecting natural ecosystems and human communities (IPCC 2014). In addition, increased urbanisation at the coasts has both costs and benefits to society, directly in terms of the risks and utility derived from where people live and work as well as indirectly through distortions to cultural heritage, use patterns, and food chains (Pelling and Blackburn 2014).

Sustainable coastal management, despite increasingly more expressive and binding legislation, increased scientific endeavor, and investment, still poses numerous implementation problems around the world (Ali et al. 2018). Proposed solutions point to a need for more integrated approaches underpinned by participative and multidisciplinary processes, which support the sustainable use of coastal resources (Henocque and Denis 2001). Emphasis is placed on coordinated approaches to better facilitate collaborative working. While concepts such as integrated coastal management and integrated coastal area management are now mature (Birch and Reyes 2018), and much has been learned from implementation practices; certain recurrent challenges are likely to feature in the management and planning for coastal zones. Examples such as working with incomplete data for the region in question, insufficient understanding of the scale at which coastal systems operate, and undertaking and aggregating simultaneous monitoring of different activities are well described in the existing literature (e.g., Cash and Moser 2000; Cornu et al. 2014). However, sustainable development cannot be attained while disasters and unsustainable practices continue to undermine economic growth and social progress (United Nations 2015), which has led to an ever-increasing demand for suitable approaches and a sound evidence base to realise both sustainability and disaster risk reduction. Earth observation (EO) has a critical role to play in helping deliver success in terms of sustainability at scale, being a source of rich spatial and temporal datasets that complement other types of data, such as census information, civil registration and vital statistics, and in situ measurements.

According to the Group on Earth Observations (GEO 2016), "Earth Observation is the gathering of information about planet Earth's physical, chemical and biological systems" using remote sensing instruments (e.g., onboard unmanned aerial vehicles (UAVs), drones, aircraft, and satellites), among others. Following the successful launch of Sputnik I in 1957, the world's first artificial satellite, and that of Vanguard 2 in 1959, the first weather satellite, satellite remote sensing for environmental research emerged as a side product of meteorology in the 1960s and its application in EO was quickly recognised (Lillesand et al. 2004). Since then, numerous EO activities have produced an unprecedented amount of data on the Earth's biosphere, lithosphere, hydrosphere, and atmosphere. Following recent technological advances in the field, and increasingly strong interest in remote sensing by the scientific community, the volume of data and the end products of said data have also increased exponentially. The European Space Agency (ESA) archive alone hosts more than 1.5 PB of data and is expected to surpass 2 PB in a few years (Nativi et al. 2015). In a similar manner to other Big Data, EO data are increasingly characterised by high volume, high velocity, and high variety, and pose requirements for veracity, value, and visualisation (Jin et al. 2015; Nativi et al. 2015). New EO-based applications and data synergies based on data-intensive science, the fourth scientific paradigm beyond empirical, theoretical, and computational science (Chen and Zhang 2014), are now possible due to new satellite systems, advanced technologies, tools, and cloud processing platforms (e.g., EU H2020 Co-ReSyF, http://co-resyf.eu/; ESA Coastal-TEP, https://coastal-tep.eo.esa.int/portal/; Amazon Web Services, https://aws.amazon.com/; Google Earth Engine, https://earthengine.google.com/). However, despite the plethora of sensors, applications, and the variability of datasets that exist, determining the relevance of remote sensing data to coastal management is still ongoing. In addition, the translation of data into knowledge that can be used by decisionmakers at different scales is still an emerging field. Therefore, while EO data, and the recent Big Data revolution, offer possible solutions to coastal management and sustainability challenges, these solutions must be part of a cohesive transdisciplinary approach rather than applied in isolation.

Extensive research into coastal sustainability issues has highlighted opportunities for EO data and technologies to support coastal management efforts, particularly in relation to environmental monitoring. Examples include wetland mapping (e.g., Adam et al. 2010; Klemas 2014); algal bloom detection (e.g., Blondeau-Patissier et al. 2014); hazard mitigation, disaster response (e.g., early warning systems (Behrens et al. 2010), and flood monitoring (De Groeve 2010; Klemas 2015*a*); land-use cover and change (e.g., Joshi et al. 2016); coastal geomorphology (e.g., Klemas 2011; Deepika et al. 2014)); maritime safety and security issues, such as vessel detection (e.g., Corbane et al. 2008; Margarit et al. 2009), and oil spill detection (e.g., Brekke and Solberg 2005; Fingas and Brown 2014); sea-state forecasting and sea level change (e.g., Dwarakish et al. 2009; Bosch et al. 2014); and urban development and coastal wetland loss (Wu et al. 2018; Rojas et al. 2019). In addition, endeavours such as Marine Spatial Planning (Ouellette and Getine 2016) and sustainable urban development at the coast (Corbane et al. 2008; Ban et al. 2015) actively incorporate multiple data sources, including EO data, to generate potential solutions to increasingly complex issues.

This paper aims to present four innovative aquatic EO applications whose relevance to the sustainable management and planning of coastal waters is currently being explored, and, using these examples, discuss the potential role EO can play in the delivery of international conventions, such as the 2030 Agenda, CBD, and Sendai Framework. By identifying potential data gaps, opportunities, and challenges, this paper begins to answer the key question of how EO can most effectively contribute to crafting options, approaches, and solutions towards sustainability (COASTS) for coastal regions of the world. Even though this paper focuses on four water applications as key examples, the authors acknowledge the existence of, and ongoing developments on, several other water, land, and climate or atmosphere EO applications that hold potential for the delivery of international conventions, but it is not within the scope of the paper to address those in detail.

## Examples of earth observation applications with relevance to coasts

Exploitation of Big EO Data enables global mapping of natural resources along the coast, ranging from fisheries, to water quality and bathymetry, as well as natural hazards, including storm surges, coastal inundation, and SLR. Four innovative advanced EO applications are presented below as examples to showcase methodological advances in different disciplines of coastal water research and oceanography.

### Application 1. Optical water types for coastal water quality monitoring

The monitoring of coastal water quality is a key requirement of national and international regulations, as well as water quality monitoring policies and programmes, such as the European Union's (EU) Water Framework Directive, USA's National Aquatic Resource Surveys — National Coastal Condition Assessment, and Australia's State of the Environment on Coastal Waters. However, ensuring that this can be done adequately and affordably remains a global challenge. In oceanic waters, where the optical complexity of the water is relatively low, the Ocean Colour suite (OC*x*) of algorithms (O'Reilly et al. 1998; ESA Climate Change Initiative Ocean Colour 2016; NASA Ocean Color Web 2019) are operationally used to produce global maps of chlorophyll-a estimates. The advantage of the OC*x* algorithm series (*x* denoting the number of wavebands used in the equation) over other ocean colour algorithms is that they work across a wide range of chlorophyll-a concentrations, and OC4 in particular provides a very high signal-to-noise ratio, and, thus, much more accurate chlorophyll-a retrievals than a variety of other empirical and semi-analytical algorithms (O'Reilly et al. 1998, 2000).

In coastal waters, several studies have shown considerable potential for the application of EO-based methods for deriving water quality estimates (see reviews by Gholizadeh et al. (2016) and Odermatt et al. (2012)) over long temporal and spatial scales (i.e., regional, continental, and, ultimately, global), but the reliable application of these methods across time and space is complicated by the diversity of water types, sensor configuration, and inherent limitations of the approaches used (e.g., atmospheric effects, adjacency effect, sun glint, sea bottom reflectance, empirical algorithm restrictions) (Brewin et al. 2015; Mouw et al. 2015; Zheng and DiGiacomo 2017). In addition, water quality retrieval in optically complex coastal waters is often determined by a combination of spatially and temporally variable properties, such as phytoplankton, suspended material, and coloured dissolved organic matter, all of which affect water colour and transparency to varying degrees. To accurately map coastal water, any operational algorithm(s) would need to account for all these properties rather than focussing on each one of them individually. For this to be achieved, prior knowledge on water typology is required to assess the partial contribution of each property to the overall water quality in the water body under investigation. Unfortunately, this knowledge is currently unavailable for most coastal regions of the world and, as a result, no single operational algorithm has been developed yet for coastal waters.

A relatively new type of classification, based on the optical properties of coastal waters, provides novel avenues for progress, and its application has recently been demonstrated with the production of the global and long-term ESA Climate Change Initiative (CCI) Ocean Colour product (www.esa-oceancolour-cci.org/). The approach clusters coastal waters into optical water types (OWTs) (Moore et al. 2001), based solely on field-, air- or space-borne spectral data (Moore et al. 2014). It has been applied in both coastal and inland water studies with very promising results (Moore et al. 2014; Trochta et al. 2015; Eleveld et al. 2017; Spyrakos et al. 2018), and is now used by ESA CCI OC v3.1 in a blended approach to map chlorophyll-a concentrations globally (ESA Climate Change Initiative Ocean Colour 2016). The advantage of OWTs is that they enable grouping of complex coastal waters based on remotely sensed optical characteristics of coastal waters that are inherently dependent upon ecology without requiring information on ecology itself (Moore et al. 2009). Even though the exact and potentially complex relationship between OWTs and coastal water ecology has not yet been investigated in depth, previous studies have demonstrated the existence of relationships between spatiotemporal distributions of OWTs and physical and biogeochemical processes and ecological diversity indices (Moore et al. 2012; Mélin and Vantrepotte 2015; Trochta et al. 2015), signifying the potential benefit from inclusion of the approach in coastal ecological monitoring and water resource management.

The innovative OWT approach not only has the potential to enable stakeholders to map water quality, such as eutrophication, and primary productivity (by using chlorophyll-a concentrations as a proxy) in coastal waters without a priori or in situ information on coastal water body ecology, and, thus, exploit global remote sensing archives for previously unmonitored sites, but to also provide users with potentially more accurate retrievals of water quality, tailored to the dynamic optical complexity of the water body in question. And while the OWT approach is becoming a powerful tool for data analysts and product developers in improving the accuracy of their EO-based water quality products, the type of information delivered to coastal water managers remains unchanged (i.e., products such as chlorophyll-a maps, or water quality indicators, such as trophic indices, are still delivered, but are more reliable). However, as tends to be the case in applications based on optical EO data, the success of the OWT approach can be limited by the effectiveness of the atmospheric correction (AC) applied to the data. There are various AC models used over coastal waters (cf. Mograne et al. 2019), such as Polymer (Steinmetz et al. 2011) and Case 2 Regional Coast Colour (C2RCC) (Doerffer and Schiller 2007), but there is no single model that works well in all cases, so improved understanding of the limitations posed by ineffective AC is required before the OWT approach can be reliably applied at global scales.

**Application 2. Species niche habitat distribution mapping**

Fisheries are crucial for food and to maintain livelihoods across the globe (FAO 2018); many coastal communities are dependent on fishing or fishing-related industries for income and food security, with fishing being a key part of their cultural identity. Using satellite-derived data to deliver effective fisheries management (e.g., approaches advocated by the international community, such as Ecosystem Approach to Fisheries Management (Chassot et al. 2011; Staples et al. 2014)) ensures access to daily, global, systematic, and high-resolution datasets for incorporating habitat considerations into marine fish population dynamics (e.g., see Druon (2010) for use of remote sensing to support conservation of the Atlantic bluefin tuna), and in particular fish species that support economies of coastal communities. Whilst satellite imagery cannot be used to identify individual fish species, it can provide critical information on the environmental pressures that shape a species population's survival success. For example, nursery habitats, such as free-floating *Sargassum* mats in the tropical Atlantic and Caribbean, which are considered as both a benefit (e.g., by providing a key fish nursery habitat (Wells and Rooker 2004)) and a hindrance (when periodic mass landings of the free-floating macroalgae strain local economies (Webster and Linton 2013; Wang and Hu 2018)). These mats can now be detected, characterized, and forecast using optical remote sensing imagery (e.g., Maréchal et al. 2017; Wang and Hu 2017; Wang et al. 2018). Hu et al. (2015) overview how remote sensing analysts can use the red-edge in satellite spectra (i.e., the comparison of high reflectance in the near-infrared region to the low reflectance in the red region of the electromagnetic spectrum, characteristic of vegetation) to remotely detect *Sargassum* presence or absence on the sea surface. However, *Sargassum* detection and quantification is often hindered by its spectral similarity to other floating organisms, materials, and often by the inadequate spatial resolution of remote sensing products. Hu et al. (2015) collected and recorded a collection of *Sargassum* spectra, noting that a distinctive reflectance, caused by the presence and levels of chlorophyll-c pigmentation in *Sargassum* tissue, can be used to effectively differentiate *Sargassum* from all other materials, provided there is a minimum of 20%–30% coverage within a satellite pixel. Wang and Hu (2017) describe how these satellite spectra records have been integrated into a *Sargassum* mapping algorithm. A stepwise process is used to eliminate all data that are of either poor quality or have very little chance of containing *Sargassum*. This is followed by conducting spectral un-mixing on *Sargassum* pixels using the spectra reported in 2015 as endmembers. By determining the fractional coverage of each pixel, distribution and area coverage maps can be produced. This process forms the basis of an automated *Sargassum* detection and biomass estimation process, underpinning the satellite-based *Sargassum* Watch System (Wang and Hu 2017). Through use of MODIS data archives, it also provisions researchers with a source of hindcast data with which to build predictive models for bloom forecasting (Wang and Hu 2017), with reported accuracies of over 80% in eastern Caribbean regions. There are limitations regarding the reliance on optical imagery, the need to adapt to cloud cover, and the lack of extensive in situ comparisons to accompany products with quality information. However, despite these limitations, this research narrative demonstrates how EO data can feed into advisory services and coastal fisheries management activities, whilst providing fisheries managers with quantifiable estimates of fish nursery habitat extents (e.g., Wang et al. 2018).

It is not only habitats that can be examined using EO. Satellite-derived data on habitat parameters can also feed into species models to understand the impacts of changes on their populations. An example of how niche characteristics, which impact a commercial species population over the course of their life cycle, can be examined and modelled is demonstrated in work done by Garrido et al. (2017). The authors clarified the influence that environmental factors measurable by satellite remote sensing had on the lifecycle of the European sardine *Sardina pilchardus*. Using satellite-derived sea surface temperature (SST) and estimates of photosynthetic activity based on chlorophyll-a measurements, the authors found that, in general, high recruitment years are associated with high chlorophyll-a and low SST levels. Such work exemplifies how actionable information can be garnered from satellite remote sensing, enabling those tasked with responsibilities for fisheries management and regulation to take appropriate management actions, and conduct more sustainable and integrated economic activities.

**Application 3. Complementary multi-platform coastal bathymetry**

Spatial data on coastal areas are key to the management of coastal and marine environments, covering aspects such as boundary and jurisdiction delineation; establishment of baseline, navigation, and seafloor change detection; issuing of consents and licences; and maintaining an inventory of coastal assets. Coastal bathymetry is an important source of spatial data used mainly for safe shipping and navigation (e.g., Jagalingam et al. 2015), marine surveying and mapping (e.g., Huang et al. 2017), but also classification of habitats and modelling of species distribution over a variety of sea floor terrains (e.g., Kostylev et al. 2003; Lundblad et al. 2006; Wilson et al. 2007). Traditionally, active remote sensing methods, such as ship-borne multi-beam echo sounder (MBES) and airborne light detection and ranging (LiDAR), have achieved accurate bathymetry results (Calder and Mayer 2003; Van Son et al. 2009; Kennedy et al. 2014). However, these conventional methods are very expensive, time-consuming, often require special permissions to work in sensitive coastal areas, and, in the case of MBES, inapplicable to shallow waters (e.g., Gao 2009; Monteys et al. 2015; Bannari and Kadhem 2017).

The complementary use of satellite EO and UAV surveying may provide a more efficient and cost-effective method of bathymetric data collection in coastal areas (Lejot et al. 2007; Klemas 2015*b*). On one hand, multispectral and hyperspectral EO data are already used as a valuable tool in deriving nearshore bathymetry (e.g., Hamylton et al. 2015). Being a non-intrusive technique, it allows for data collection, and the consequent production of bathymetry and seafloor maps, without causing any disturbance to local wildlife and ecosystems. On the other hand, UAVs provide the opportunity to fill data gaps and act as a validation technique to existing EO data products. UAVs, in particular, helicopter platforms, offer increased mobility, hover capabilities, and lower operating costs compared to conventional high-spatial-resolution data capture methods (Klemas 2015*b*). Collection of spectral data concurrent with satellite pass-over times allows for cross-calibration and validation of processed satellite data. This complementary duel approach has the potential to provide many benefits: low cost, operational flexibility and versatility, ground truth data, reduction of the influence of cloud cover, and surveying of typically inaccessible coastal waters and coastal terrain (Long et al. 2016). However, satellite- and UAV-derived bathymetry data are still susceptible to limitations based on AC inefficiencies and coastal complexities that hinder the optical bottom signal detected at the water surface (Gao 2009; Pacheco et al. 2015). Distortion of the spectral signature due to turbid waters and (or) biota coverage, such as seagrass, proves a challenging restraint to the application of satellite-derived bathymetry across broad coastal areas (Gao 2009; Caballero et al. 2019). Research into the impacts of such coastal complexities on satellite-derived bathymetry and accompanying depth limitations is required to determine confidence levels and identify optimum algorithms (Halls and Costin 2016; Caballero et al. 2019). Integrating high-resolution optical remote sensing with habitat classification data to ascertain the relationship between water reflectance, water depth, and seafloor habitat coverage is used to demonstrate the production of complementary bathymetry and habitat data from satellite data (Lyons et al. 2011; Traganos et al. 2018), with successful applications in coral reef bathymetry (Huang et al. 2017) and seagrass mapping (Hossain et al. 2015). Bathymetric mapping of valuable substrate, such as coral reefs, is a useful tool for monitoring vulnerable areas or areas that undergo topographic change (Vanderstraete et al. 2003) and ESA's Sentinel-2 satellite captures nearly 90% of the world's coral reefs, providing vast potential for high-resolution monitoring of benthic change (Hedley et al. 2018).

The cost-effective repeatability of coastal bathymetry products through EO and UAV multispectral data collection offers vast improvements to coastal management challenges and ecosystem monitoring, and offers invaluable up-to-date insights into how shorelines respond to climate change events, globally. An ever-increasing fleet of optical EO satellites, and advancements in UAV technology, can only improve the collection, processing, and production of accurate and reliable coastal bathymetry products.

**Application 4. Coastal inundation mapping and prediction, and storm surge risk assessment**

Changing climates and increased variability present many threats and risks to both human and biophysical systems at multiple scales across the globe; this means that integrating short-term disaster risk reduction measures with long-term climate change adaptation is an ever-increasing priority. One of the challenges with integrated risk management approaches remains identifying climate variables and developing robust, reliable, long-term climate observations linked with extreme events (EEA 2017). In response to this challenge, the Global Climate Observing System has identified 54 essential climate variables (WMO 2016) several of which can be derived from satellite EO data (Hollmann et al. 2013).

Sea level has been identified as an essential climate variable. SLR has historically been measured using coastal tide gauges; however, the development of satellite altimeters has enabled the extrapolation of measurements further offshore providing a wider, consistent spatial context at global scales as well as a greater understanding of casual factors (Ablain et al. 2015). Long-term trends in SLR can now be derived from over 50 years of combined in situ and remote sensing data (Cabanes et al. 2001). The applicability of remote sensing in mapping SLR at global scales has also been demonstrated for a 20-year period (1995–2015) by the ESA CCI Sea Level product (www.esa-sealevel-cci.org/). Furthermore, work by Nicholls and Cazanave (2010) demonstrated the capability to supplement long-term trend estimates with quantifications of regional variability. This ability to translate global trends down to sea basins and regional shorelines allows responsive adaptive management across both temporal and spatial scales.

Even though satellite altimetry is a mature technology for studying open oceans, near-coastal applications are impeded because of mixed pixels and contaminated return signals caused by hard surfaces, such as nearshore rocky outcrops and coastal infrastructure; this results in unreliable sea level estimates close to the coast (Vignudelli et al. 2005). However, altimetry specialists have begun extracting usable information from data previously considered to be of poor quality. For instance, total water level envelope estimates (i.e., the sea surface level taking into account tides, waves, effects of a storm surge, and (usually) precipitation and river flows) can now be extracted up to a distance of 3 km from the shoreline, a distance that is decreasing as sensor capabilities and processing algorithms improve (Vignudelli et al. 2011). Despite these advancements, the establishment of targeted nearshore (i.e., 3–50 km from the coastline) and offshore (further than 50 km from the coastline) sea level monitoring sites allowing for direct satellite-to-field measurement comparisons would be beneficial to gauge the accuracy of satellite-derived sea level data.

In addition to SLR, one of the most promising applications of coastal altimetry is in the study of storm surges (Cipollini et al. 2014). Impacts from storm surges and associated coastal flooding events are anticipated to increase in severity (e.g., for the Atlantic, see Bernier and Thompson (2006) and Tebaldi et al. (2012)) and so reliable modelling of storm surges can support both preparation and mitigation activities by improving understanding of how waves propagate and impact on coastal infrastructure. Improvements in this understanding could bring enormous societal benefits, particularly to populated low-elevation coastal zones. Research by Madsen et al. (2015) demonstrated how, using a stationary blending method, coastal satellite altimetry data can be related with corresponding tide gauge measurements, allowing generation of sea level maps and reducing storm surge forecast error. Liu et al. (2018) developed a risk and vulnerability assessment approach combining coastal hydrological observations, numerical storm surge modelling, and multi-source remote sensing data to map coastal infrastructure and land use. This approach was then used to assess overall risk of storm surges. Another example includes the use of UAVs to estimate the extent of coastal flooding and assess damages in critical areas demonstrating innovative EO capacities in the support of coastal hazard risk management activities (Popescu et al. 2017).

## Supporting the delivery of international conventions through EO

The 2015 adoption of these landmark UN agreements, in combination with the CBD (1992), the COP21's Paris Climate Conference (2015), and Habitat III's New Urban Agenda (2017) created a significant opportunity to build coherence across overlapping social and ecological policy spaces. The lack of integration across strategies, policies, and implementation has long been perceived as one of the main barriers to more sustainable development (International Council for Science 2017). Insufficient accounting for trade-offs and synergies at multiple scales has resulted in incoherence, adverse and unexpected impacts, and ultimately in diverging outcomes and trends across global objectives for sustainable development (Neumann et al. 2017). However, when taken in combination, this new suit of frameworks covers a more comprehensive resilience agenda spanning development, humanitarian, climate, and disaster risk reduction areas.

This reality implies a need for greater cohesion at the implementation level. The previous section of this paper presented four novel and rapidly advancing EO applications with strong relevance to various aspects of coastal sustainability and management. These four example applications also highlight the potential for EO data and derived information to supplement and support the simultaneous delivery of multiple indicators, targets, and goals of different international conventions, such as 2030 Agenda, the Sendai Framework, and the CBD (Table 1). The inherent interconnectedness of many of the goals and targets of international conventions demonstrate the potential for added value when applying technologies, such as EO, to support implementation. As shown in Table 1, the four EO applications described in this study can indirectly and directly support 19 UN SDG indicators pertaining to SD Goals 1, 2, 6, 11, 12, 13, and 14. This is in agreement with a similar synthesis performed by the international initiative "Earth Observations for the Sustainable Development Goals (EO4SDG)" on the most likely UN SDG targets and indicators to which EO can contribute (GEO 2016). Many of the same EO-based data and information products can also be used to inform and support five Sendai Targets (12 Sendai indicators) and two CDB Goals (six CBD targets) (Table 1).

It should be noted that EO data and information can contribute indirectly (i.e., support) or directly (i.e., measurement) to the above-mentioned indicators, targets, and goals. For example, indirect contribution can be demonstrated using SDG2 Target 2.4, Indicator 2.4.1 "Proportion of agricultural area under productive and sustainable agriculture". Agricultural runoff is a major cause of eutrophication and deterioration of water quality in coastal areas (Ongley 1996). Water quality measurements provide an indicator of the nature and health of an ecosystem and degraded water quality can lead to a reduction in marine biodiversity (Jackson 2008) as well as dramatically impact quality and quantity of ecosystem services (Barbier et al. 2011) leading to knock-on effects on human health and well-being (Myers et al. 2013). Quantifying the amount of land under agricultural use in coastal zones is therefore a key baseline statistic that can be used as a proxy for non-point-source pollution, and EO-based land cover and use mapping can play an important role in this. By supplementing that knowledge with information on coastal water quality and trophic status along coastlines (see section entitled "Application 1. Optical water types for coastal water quality monitoring"), targeted action toward better management of agricultural runoff and establishment of measures for sustainable agriculture can be taken to

**Table 1.** International goals, targets, and indicators to which each identified EO application can contribute data and information: SDG, United Nations Sustainable Development Goals; Sendai, Sendai Framework for Risk Reduction; and CBD, Convention on Biological Diversity.

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| Optical water types for coastal water quality monitoring | Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture | 2.4 — Ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality | 2.4.1 — Proportion of agricultural area under productive and sustainable agriculture | | | B — Reduce the direct pressures on biodiversity and promote sustainable use | 8 — Pollution, including from excess nutrients, has been brought to levels that are not detrimental to ecosystem function and biodiversity |
| | Goal 6. Ensure availability and sustainable management of water and sanitation for all | 6.3 — Improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally | 6.3.2 — Proportion of bodies of water with good ambient water quality | | | D — Enhance the benefits to all from biodiversity and ecosystem services | 14 — Ecosystems that provide essential services, including services related to water, and contribute to health, livelihoods and well-being, are restored and safeguarded, taking into account the needs of women, indigenous and local communities, and the poor and vulnerable |
| | | 6.5 — Implement integrated water resources management at all levels, including through transboundary cooperation as appropriate | 6.5.2 — Proportion of transboundary basin area with an operational arrangement for water cooperation | | | | |
| | Goal 14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development | 14.1 — Prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution | 14.1.1 — Index of coastal eutrophication and floating plastic debris density | | | | |

**Table 1.** (*continued*).

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| Species niche habitat distribution mapping | Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture | 2.4 — Ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality | 2.4.1 — Proportion of agricultural area under productive and sustainable agriculture | | | B — Reduce the direct pressures on biodiversity and promote sustainable use | 5 — The rate of loss of all natural habitats, including forests, is at least halved and where feasible brought close to zero, and degradation and fragmentation is significantly reduced<br>6 — All fish and invertebrate stocks and aquatic plants are managed and harvested sustainably, legally and applying ecosystem based approaches, so that overfishing is avoided, recovery plans and measures are in place for all depleted species, fisheries have no significant adverse impacts on threatened species and vulnerable ecosystems and the impacts of fisheries on stocks, species and ecosystems are within safe ecological limits |
| | Goal 12. Ensure sustainable consumption and production patterns | 12.a — Support developing countries to strengthen their scientific and technological capacity to move towards more sustainable patterns of consumption and production | 12.a.1 — Amount of support to developing countries on research and development for sustainable consumption and production and environmentally sound technologies | | | | |
| | Goal 14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development | 14.4 — Effectively regulate harvesting and end overfishing, illegal, unreported and unregulated fishing and destructive fishing practices and implement science-based management plans, in order to restore fish stocks in the shortest time feasible, at least to levels that can produce maximum sustainable yield as determined by their biological characteristics | 14.4.1 — Proportion of fish stocks within biologically sustainable levels | | | D — Enhance the benefits to all from biodiversity and ecosystem services | 14 —Ecosystems that provide essential services, including services related to water, and contribute to health, livelihoods and well-being, are restored and safeguarded, taking into account the needs of women, indigenous and local communities, and the poor and vulnerable |





Published by Canadian Science Publishing in partnership with East China Normal University

**Table 1.** (*continued*).

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| | | 14.7 — Increase the economic benefits to small island developing States and least developed countries from the sustainable use of marine resources, including through sustainable management of fisheries, aquaculture and tourism | 14.7.1 — Sustainable fisheries as a proportion of GDP in small island developing States, least developed countries and all countries | | | | |
| Complementary multi-platform coastal bathymetry | Goal 14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development | 14.5 — Conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information | 14.5.1 — Coverage of protected areas in relation to marine areas | | | B — Reduce the direct pressures on biodiversity and promote sustainable use | 10 — The multiple anthropogenic pressures on coral reefs, and other vulnerable ecosystems impacted by climate change or ocean acidification are minimized, so as to maintain their integrity and functioning |
| | | 14.7 — Increase the economic benefits to small island developing States and least developed countries from the sustainable use of marine resources, including through sustainable management of fisheries, aquaculture and tourism | 14.7.1 — Sustainable fisheries as a proportion of GDP in small island developing States, least developed countries and all countries | | | D — Enhance the benefits to all from biodiversity and ecosystem services | 14 — Ecosystems that provide essential services, including services related to water, and contribute to health, livelihoods and well-being, are restored and safeguarded, taking into account the needs of women, indigenous and local communities, and the poor and vulnerable |
| | | | | | | | 15 — Ecosystem resilience and the contribution of biodiversity to carbon stocks has been enhanced, through conservation and restoration, including restoration of at least 15 per cent of degraded ecosystems, thereby contributing to climate change mitigation and adaptation and to combating desertification |

**Table 1.** (*continued*).

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| Coastal inundation mapping and prediction, and storm surge risk assessment | Goal 1. End poverty in all its forms everywhere | 1.5 — Build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters | 1.5.1 — Number of deaths, missing persons and directly affected persons attributed to disasters per 100 000 population<br>1.5.2 — Direct economic loss attributed to disasters in relation to global gross domestic product (GDP)<br>1.5.3 — Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030<br>1.5.4 — Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies | A —Substantially reduce global disaster mortality by 2030, aiming to lower average per 100 000 global mortality between 2020–2030 compared with 2005–2015 | A-1 — Number of deaths and missing persons attributed to disasters, per 100 000 population | D — Enhance the benefits to all from biodiversity and ecosystem services | 14 — Ecosystems that provide essential services, including services related to water, and contribute to health, livelihoods and well-being, are restored and safeguarded, taking into account the needs of women, indigenous and local communities, and the poor and vulnerable<br>15 —Ecosystem resilience and the contribution of biodiversity to carbon stocks has been enhanced, through conservation and restoration, including restoration of at least 15 per cent of degraded ecosystems, thereby contributing to climate change mitigation and adaptation and to combating desertification |
| | Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture | 2.4 — Ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality | 2.4.1 — Proportion of agricultural area under productive and sustainable agriculture | B —Substantially reduce the number of affected people globally by 2030, aiming to lower the average global figure per 100 000 between 2020–2030 compared with 2005–2015 | B-1 — Number of directly affected people attributed to disasters, per 100 000 population<br>B-3 — Number of people whose damaged dwellings were attributed to disasters<br>B-4 — Number of people whose destroyed dwellings were attributed to disasters | | |



Published by Canadian Science Publishing in partnership with East China Normal University

**Table 1.** (*continued*).

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| | Goal 11. Make cities and human settlements inclusive, safe, resilient and sustainable | 11.5 — Significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations | 11.5.1 — Number of deaths, missing persons and directly affected persons attributed to disasters per 100 000 population<br>11.5.2 — Direct economic loss in relation to global GDP, damage to critical infrastructure and number of disruptions to basic services, attributed to disasters | C —Reduce direct disaster economic loss in relation to global gross domestic product | C-3 — Direct economic loss to all other damaged or destroyed productive assets attributed to disasters<br>C-4 — Direct economic loss in the housing sector attributed to disasters<br>C-5 — Direct economic loss resulting from damaged or destroyed critical infrastructure attributed to disasters<br>C-6 — Direct economic loss to cultural heritage damaged or destroyed attributed to disasters | | |
| | | 11.b — Substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, resilience to disasters, and develop and implement, in line with the Sendai Framework, holistic disaster risk management at all levels | 11.b.1 — Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030<br>11.b.2 — Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies | D —Substantially reduce disaster damage to critical infrastructure and disruption of basic services, among them health and educational facilities, including through developing their resilience by 2030 | D-1 — Damage to critical infrastructure attributed to disasters<br>D-5 — Number of disruptions to basic services attributed to disasters | | |

**Table 1.** (*concluded*).

| EO application | SDG | SDG target | SDG indicator | Sendai target | Sendai indicator | CBD goal | CBD target |
|---|---|---|---|---|---|---|---|
| | Goal 13. Take urgent action to combat climate change and its impacts | 13.1 — Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries | 13.1.1 — Number of deaths, missing persons and directly affected persons attributed to disasters per 100 000 population<br>13.1.2 — Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030<br>13.1.3 — Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies | G —Substantially increase the availability of and access to multi-hazard early warning systems and disaster risk information and assessments | G-5 — Number of countries that have accessible, understandable, usable and relevant disaster risk information and assessment available to the people at the national and local levels<br>G-6 — Percentage of population exposed to or at risk from disasters protected through pre-emptive evacuation following early warning | | |

improve overall ecosystem health and tackle biodiversity loss. Therefore, the task of enhancing EO-based land cover and use data with accurate OWT-based water quality retrievals can help support the implementation of both SDG Indicator 2.4.1 and CDB Target B.8. In fact, in most cases presented in Table 1, the role of EO is supportive and supplementary to overall implementation.

There are also cases where EO measurements can directly contribute to an indicator, such as in the case of SDG6 Target 6.3 Indicator 6.3.2 "Proportion of bodies of water with good ambient water quality". EO has been used for decades as a tool for local, regional, and global coastal water monitoring. The most recent technological and methodological advances (e.g., see section entitled "Application 1. Optical water types for coastal water quality monitoring") have shown great promise for coastal water quality retrievals (e.g., Moore et al. 2014) and various initiatives are now engaging local and national stakeholders and decisionmakers to build trust and capacity in EO-based water monitoring (e.g., Paterson et al. 2018; UN Environment 2018) and explore the implementation of the SDGs using EO at the regional level (e.g., Plag and the Workshop Participants 2018).

While there are numerous benefits of using EO technology as an operational support tool for sustainability planning, implementation, and monitoring, there is an acceptance that EO data are not a one-size-fits-all solution to increased coastal sustainability and improved management. The incorporation of EO data can complement existing spatiotemporal data collections as well as allow for inaccessible areas to be more efficiently monitored and managed, but these data must be used in conjunction with in situ social and biophysical datasets.

## Recognising challenges, and opportunities, with EO data use

Whilst international conventions are signed at the global level, actions and successes take place at national and sub-national scales. However, *limited capacity and capabilities*, both human and technical, drive the disparity in current EO use across regions (north versus south and west versus east) and restrict much of the potential uses of EO applications at national and sub-national scales, especially in the global south (Vanhove et al. 2017) (i.e., countries seen as low and middle income in Asia, Africa, Latin America, and the Caribbean by the World Bank). In addition, the translation of the relevance of technical applications such as EO to decision support knowledge, along with language surrounding multiple monitoring and evaluation mechanisms, such as the indicators and targets described in Table 1, is often a difficult link to make. Also, past experiences of a variety of state actors, working for various state agencies, have resulted in a continued express of concern around data sources, data processing, and uses of data (EDPS 2015); this has resulted in mistrust and political rejection of methodologies, technologies, and data products (von Maurich and Golkar 2018), highlighting the added issue of *limited institutional acceptance* of EO data and information.

Beyond issues stemming from lack of infrastructure and capacity, product accuracy, and reliability, lack of validation data, data continuity, and cost have been identified as main reasons as to why management decisions do not typically rely on EO-derived water quality products, according to a recent survey that was conducted within the USA Environmental Protection Agency (Schaeffer et al. 2013). *Product accuracy and reliability* and *lack of suitable validation data* are issues that the EO community has begun to address in recent years. Through interaction with users and stakeholders, and collaborations with in situ data holders, EO products have become more accurate and application-driven as, for example, in the case of the ESA CCI programme (http://cci.esa.int/) and projects such as EU H2020 CyanoAlert (www.cyanoalert.com/), EU H2020 CoastObs (https://coastobs.eu/), and ESA Thematic Exploitation Platforms (TEPs; https://tep.eo.esa.int/). Large and open access marine and terrestrial data repositories of in situ measurements, for example, SeaDataNet (www.seadatanet.org/), EMODnet (www.emodnet.eu/), Argo (www.argo.ucsd.edu/index.html), Global Ocean Observing System (GOOS; www.goosocean.org/), and International Soil Moisture Network (ISMN; https://ismn.geo.tuwien.ac.at/) serve as sources of validation data for water and land remote sensing. Examples of large-scale validation efforts include ESA MERMAID (http://mermaid.acri.fr/home/home.php); a centralised database of merged in situ optical measurements and concurrent ENVISAT MERIS acquisitions for ocean research, UK NERC LIMNADES (www.limnades.org/home.psp); a centralised database of worldwide bio-optical measurements and match-up data for remote sensing, and EU H2020 MONOCLE (www.monocle-h2020.eu/Home); a project that is currently developing in situ observation solutions for EO-based coastal and inland water quality. Finally, the Group on Earth Observations "system of systems" approach (GEOSS; www.earthobservations.org/geoss.php) combines information from different sources and promotes common technical standards so that different datasets can be combined in a coherent manner towards advancement of EO techniques and applications.

*Sensor discontinuity* has in the past affected the remote sensing community. In the field of ocean colour and water monitoring, the most recent example was when ENVISAT MERIS unexpectedly failed in April 2012 creating a 4 year data gap in medium spatial resolution, multi-spectral EO-based water monitoring until the launch of its successor Sentinel-3A OLCI in February 2016. However, the consensus on this is changing and space agencies have started developing satellite sensors that offer continuity to previous missions, with one of the best examples of this effort being the NASA–USGS (US Geological Survey) Landsat-series. At the same time, methodological advances enable researchers to better harmonise datasets from different instruments and, thus, generate merged long-term datasets, such as the global multi-decadal products of the ESA CCI programme (see, e.g., the Soil Moisture (Dorigo et al. 2017) and Ocean Colour (Mélin et al. 2017) products). Furthermore, these methodological advances are coupled with a recent increase in free data provision by large initiatives, such as the European Copernicus programme (http://copernicus.eu/), providing long-term spatially explicit time series of free applications-focused data.

Challenges that exist around barriers to effective data access, sharing, management, storage, and usage are numerous and complex. Many *institutional and financial barriers to data access* exist, including costs for data already collected and processed, often with public funding, and license conditions on the use of the data and publication of results (Beniston et al. 2012). In some cases, for example, data collected may be highly political and beyond the influence of the scientific community (Giuliani et al. 2017; L. Zhang et al. 2018) and in other cases there may be geographical or temporal sparseness of data reducing utility (Espey et al. 2015; Plag and the Workshop Participants 2018). In the case of the USGS Landsat archive, recent considerations around changing the open data access policy to cost-sharing models (LAG 2019) could mean that the current free access to the longest environmental satellite archive may be restrained by one's budget in the future and, thus, restricting data use and stifling innovation and business activity (NGAC 2012). In addition, limited investment to centralise or secure different types of data, and (or) storing the same type of data in various formats with little compatibility can create cascading issues across potential or actual users. While there are examples of efforts under way in Europe to remove the obstacles and costs related to data access for the purposes of research and policy-making, in particular, the European INSPIRE Directive of 2007 (http://inspire.jrc.ec.europa.eu/), the trajectory of progress is still slow and additional efforts are still needed by most EU Member States towards identification of spatial datasets, provision of services for access to spatial data and alignment of spatial data with regards to the common data models under INSPIRE (Cetl et al. 2017).

In recent years, EO organisations and funding bodies have begun to address some of the abovementioned issues and challenges by attempting to utilise cloud computing as a means of allowing access to EO data and processing capabilities under intuitive cloud processing platforms (e.g., EU H2020 Co-ReSyF and ESA TEPs). This emerging trend of thematically dedicated EO cloud platforms aims to provide virtual environments which not only facilitate the use of EO data for thematic research (e.g., coastal, but also urban, forestry, geohazards, and food security), but also broaden the uptake of EO data use in scientific communities by providing improved processing capabilities, easier data access, and more accessible infrastructure. A key step in the initiation of said platforms is stakeholder engagement within the scientific community. Building services based on stakeholder needs and recommendations not only ensures relevant and sustainable platform development but it also serves to engage, educate, and animate the wider community with regard to the capabilities of EO.

Finally, one of the most common limitations of optical (see the sections entitled *Application 1. Optical water types for coastal water quality monitoring*; *Application 2. Species niche habitat distribution mapping*; and *Application 3. Complementary multi-platform coastal bathymetry*) and thermal (e.g., used for SST — see the section entitled *Application 2. Species niche habitat distribution mapping*) remote sensing applications is the effectiveness of the AC applied to the EO data. In turbid coastal waters, standard AC models often exhibit large inaccuracies (Fan et al. 2017) and previous studies have shown that not one single AC works in all cases (e.g., Larnicol et al. 2018; M. Zhang et al. 2018). However, AC models, such as the Polymer and C2RCC have shown great potential in optically complex waters (Mograne et al. 2019), such as those found in coastal areas, and it may be the case that different ACs are suited for different regions, coastal water bodies or applications. For example, the image correction for atmospheric effects (iCOR) algorithm was developed for both land and water pixels to reduce discontinuities in reflectance caused by separate application of water- and land-specific AC within one scene (De Keukelaere et al. 2018), and could therefore be a suitable option for transitional areas, such as the coastal zone.

## Discussion and conclusions

There is a growing realisation and acceptance that sustainable development cannot be attained while disasters and unsustainable practices continue to undermine economic growth and social progress at many scales (United Nations 2015); this remains most pertinent in the coastal zones of the world. This reality has led to an ever-increasing demand from decision makers and planners alike for salient, near-real-time information and decision-support tools that can provide a sound evidence base to help enable the realisation of both the sustainability and the disaster risk reduction agendas in tandem. Earth observation holds much unrealised potential in data and knowledge provision in the field of coastal management. Data inaccuracy, cost, and discontinuity have in the past prohibited long-term and reliable retrievals of EO data, but this is changing. With the recent open data policy adopted by large space agencies around the world (e.g., NASA and ESA), users can now freely download the full archives of satellite sensors, including the 40 year long NASA–USGS Landsat archive and the new Copernicus Sentinel-series datasets. In addition, a variety of EO products with known and improved accuracies now exist (see, e.g., the ESA Climate Change Initiative programme) and the remote sensing community, supported by global initiatives, such the Group on Earth Observations, has been tackling issues such as product validation and AC to further improve product accuracy and uptake. With user engagement initiatives and related funding opportunities also increasing in number in the last few years, there has been an increase in contributions towards building national capacity around the world and overcoming obstacles, such as lack of infrastructure and training. Examples include the ESA-funded "Utilising Earth Observation to support Blue Growth and Risk Management in the Caribbean", which coupled capacity building with user engagement and consultation (Scarrott et al. 2018) to produce a stakeholder-led set of actions and a roadmap (Paterson et al. 2018) for enhancing EO support for targeted coastal issues and opportunities.

This paper clearly demonstrates that EO can be used to provide a more synoptic view of coastal water systems that can support and enhance sustainable management. While this paper has focused on only four innovative applications, there exist many more satellite EO-based applications that should also be considered and integrated into efforts towards the implementation of sustainable management practices. As it was not the intention of this study to list all suitable, or potentially suitable, EO applications covering water, land, and air in the coastal zone, we used four coastal applications as key examples to demonstrate the applicability of EO for coastal sustainable management and discuss associated challenges. There is also a strong case for the increased use of archived EO datasets to analyse long-term trends now that improved technical cloud processing-based applications are becoming more user-friendly, and data are becoming more accessible through shifting data sharing practices. The paper also demonstrates the value of EO applications in supporting the implementation of multiple policy instruments and conventions that are currently driving the global transition to sustainable development, both as stand-alone sources of information and as complementary data sources to more traditional in situ collections. This, in turn, emphasises the importance of transdisciplinary collaborations to realise the full potential to transform existing management practices and access as-yet undefined solution spaces within coastal management.

## Acknowledgements

This work was supported by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 687289 (Co-ReSyF project), the United Kingdom's Natural Environment Research Council (NERC) under Grant NE/E009328 (GloboLakes project), and the Future Earth Coasts project. The authors would like to thank the two anonymous reviewers for their comments that led to improvement of the manuscript.

## References

Ablain, M., Cazenave, A., Larnicol, G., Balmaseda, M., Cipollini, P., Faugère, Y., et al. 2015. Improved sea level record over the satellite altimetry era (1993–2010) from the Climate Change Initiative project. Ocean Sci. **11**: 67–82. doi: 10.5194/os-11-67-2015.

Adam, E., Mutanga, O., and Rugege, D. 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. Wetlands Ecol. Manage. **18**(3): 281–296. doi: 10.1007/s11273-009-9169-z.

Ali, S., Darsan, J., Singh, A., and Wilson, M. 2018. Sustainable coastal ecosystem management — An evolving paradigm and its application to Caribbean SIDS. Ocean Coastal Manage. **163**(1): 173–184. doi: 10.1016/j.ocecoaman.2018.06.004.

Ban, Y., Jacob, A., and Gamba, P. 2015. Spaceborne SAR data for global urban mapping at 30 m resolution using a robust urban extractor. ISPRS J. Photogramm. Remote Sens. **103**: 28–37. doi: 10.1016/j.isprsjprs.2014.08.004.

Bannari, A., and Kadhem, G. 2017. MBES-CARIS data validation for bathymetric mapping of shallow water in the Kingdom of Bahrain on the Arabian Gulf. Remote Sens. **9**(4): 385. doi: 10.3390/rs9040385.

Barbier, E.B., Hacker, S.D., Kennedy, C., Koch, E.W., Stier, A.C., and Silliman, B.R. 2011. The value of estuarine and coastal ecosystem services. Ecol. Monogr. **81**(2): 169–193. doi: 10.1890/10-1510.1.

Behrens, J., Androsov, A., Babeyko, A.Y., Harig, S., Klaschka, F., and Mentrup, L. 2010. A new multi-sensor approach to simulation assisted tsunami early warning. Nat. Hazards Earth Syst. Sci. **10**(6): 1085–1100. doi: 10.5194/nhess-10-1085-2010.

Beniston, M., Stoffel, M., Harding, R., Kernan, M., Ludwig, R., Moors, E., et al. 2012. Obstacles to data access for research related to climate and water: Implications for science and EU policy-making. Environ. Sci. Policy, **17**: 41–48. doi: 10.1016/j.envsci.2011.12.002.

Bernier, N.B., and Thompson, K.R. 2006. Predicting the frequency of storm surges and extreme sea levels in the northwest Atlantic. J. Geophys. Res.: Oceans, **111**(C10): C10009. doi: 10.1029/2005JC003168.

Birch, T., and Reyes, E. 2018. Forty years of coastal zone management (1975–2014): Evolving theory, policy and practice as reflected in scientific research publications. Ocean Coastal Manage. **153**: 1–11. doi: 10.1016/j.ocecoaman.2017.12.003.

Blondeau-Patissier, D., Gower, J.F.R., Dekker, A.G., Phinn, S.R., and Brando, V.E. 2014. A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. Prog. Oceanogr. **123**: 123–144. doi: 10.1016/j.pocean.2013.12.008.

Bosch, W., Dettmering, D., and Schwatke, C. 2014. Multi-mission cross-calibration of satellite altimeters: Constructing a long-term data record for global and regional sea level change studies. Remote Sens. **6**(3): 2255–2281. doi: 10.3390/rs6032255.

Brekke, C., and Solberg, A.H.S. 2005. Oil spill detection by satellite remote sensing. Remote Sens. Environ. **95**(1): 1–13. doi: 10.1016/j.rse.2004.11.015.

Brewin, R.J.W., Sathyendranatha, S., Müller, D., Brockmann, C., Deschamps, P.-Y., Devred, E., et al. 2015. The Ocean Colour Climate Change Initiative: III. A round-robin comparison on in-water bio-optical algorithms. Remote Sens. Environ. **162**: 271–294. doi: 10.1016/j.rse.2013.09.016.

Caballero, I., Stumpf, R.P., and Meredith, A. 2019. Preliminary assessment of turbidity and chlorophyll impact on bathymetry derived from Sentinel-2A and Sentinel-3A satellites in South Florida. Remote Sens. **11**(6): 645. doi: 10.3390/rs11060645.

Cabanes, C., Cazenave, A., and Le Provost, C. 2001. Sea level rise during past 40 years determined from satellite and in situ observations. Science, **294**: 840–842. doi: 10.1126/science.1063556. PMID: 11679666.

Calder, B.R., and Mayer, L.A. 2003. Automatic processing of high-rate, high-density multibeam echosounder data. Geochem., Geophys., Geosyst. **4**(6): 1048. doi: 10.1029/2002GC000486.

Cash, D.W., and Moser, S.C. 2000. Linking global and local scales: Designing dynamic assessment and management processes. Global Environ. Change, **10**(2): 109–120. doi: 10.1016/S0959-3780(00)00017-0.

Central Intelligence Agency. 2016. The world factbook 2016–17: Geography: World: Geographic overview: Coastline. Central Intelligence Agency, Washington, D.C., USA.

Cetl, V., Nunes de Lima, V., Tomas, R., Lutz, M., D'Eugenio, J., Nagy, A., and Robbrecht, J. 2017. Summary report on status of implementation of the INSPIRE Directive in EU, EUR 28930 EN. Publications Office of the European Union, Luxembourg, Luxembourg. ISBN 978-92-79-77058-6. doi: 10.2760/143502.

Chassot, E., Bonhommeau, S., Reygondeau, G., Nieto, K., Polovina, J.J., Huret, M., et al. 2011. Satellite remote sensing for an ecosystem approach to fisheries management. ICES J. Mar. Sci. **68**(4): 651–666. doi: 10.1093/icesjms/fsq195.

Chen, C.L.P., and Zhang, C.-Y. 2014. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. Inf. Sci. **275**: 314–347. doi: 10.1016/j.ins.2014.01.015.

Chmura, G., Anisfeld, S., Cahoon, D., and Lynch, J. 2003. Global carbon sequestration in tidal, saline wetland soils. Global Biogeochem. Cycles, **17**(4): 1111. doi: 10.1029/2002GB001917.

Cipollini, P., Scarrott, R.G., and Snaith, H. 2014. Product data handbook: Coastal altimetry. Issue 2.0. *Produced by* the eSurge project under ESA-ESRIN contract number 4000103880/11/I-LG. Available from http://www.storm-surge.info/product-handbooks [accessed 28 August 2019].

Convention on Biological Diversity (CBD). 1992. The Convention on Biological Diversity. United Nations, Rio de Janeiro, Brazil. Available from https://www.cbd.int/convention [accessed 11 July 2018].

Corbane, C., Marre, F., and Petit, M. 2008. Using SPOT-5 HRG data in panchromatic mode for operational detection of small ships in tropical area. Sensors, **8**(5): 2959–2973. doi: 10.3390/s8052959. PMID: 27879859.

Cornu, E.L., Kittinger, J.N., Koehn, J.Z., Finkbeiner, E.M., and Crowder, L.B. 2014. Current practice and future prospects for social data in coastal and ocean planning. Conserv. Biol. **28**: 902–911. doi: 10.1111/cobi.12310. PMID: 24779578.

De Groeve, T. 2010. Flood monitoring and mapping using passive microwave remote sensing in Namibia. Geomatics Nat. Hazards Risk, **1**(1): 19–35. doi: 10.1080/19475701003648085.

De Keukelaere, L., Sterckx, S., Adriaensen, S., Knaeps, E., Reusen, I., Giardino, C., et al. 2018. Atmospheric correction of Landsat-8/OLI and Sentinel-2/MSI data using iCOR algorithm: Validation for coastal and inland waters. Eur. J. Remote Sens. **51**(1): 525–542. doi: 10.1080/22797254.2018.1457937.

Deepika, B., Avinash, K., and Jayappa, K. 2014. Shoreline change rate estimation and its forecast: Remote sensing, geographical information system and statistics-based approach. Int. J. Environ. Sci. Technol. **11**(2): 395–416. doi: 10.1007/s13762-013-0196-1.

Doerffer, R., and Schiller, H. 2007. The MERIS case 2 water algorithm. Int. J. Remote Sens. **28**: 517–535. doi: 10.1080/01431160600821127.

Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., et al. 2017. ESA CCI soil moisture for improved Earth system understanding: State-of-the art and future directions. Remote Sens. Environ. **203**: 185–215. doi: 10.1016/j.rse.2017.07.001.

Druon, J.N. 2010. Habitat mapping of the Atlantic Bluefin tuna derived from satellite data: Its potential as a tool for the sustainable management of pelagic fisheries. Mar. Policy, **34**(2): 293–297. doi: 10.1016/j.marpol.2009.07.005.

Dwarakish, G.S., Vinay, S.A., Natesan, U., Asano, T., Kakinuma, T., Venkataramana, K., et al. 2009. Coastal vulnerability assessment of the future sea level rise in Udupi coastal zone of Karnataka state, west coast of India. Ocean Coastal Manage. **52**(9): 467–478. doi: 10.1016/j.ocecoaman.2009.07.007.

Eleveld, M.A., Ruescas, A.B., Hommersom, A., Moore, T.S., Peters, S.W.M., and Brockmann, C. 2017. An optical classification tool for global lake waters. Remote Sens. **9**(5): 420. doi: 10.3390/rs9050420.

ESA Climate Change Initiative Ocean Colour. 2016. Algorithm theoretical baseline document (ocean colour algorithm blending) version 1.0, 21 March. Plymouth Marine Laboratory, Plymouth, UK. Available from http://www.esa-oceancolour-cci.org/?q=documents [accessed 26 October 2018].

Espey, J., Swanson, E., Badiee, S., Christensen, Z., Fischer, A., Levy, M. et al. 2015. Data for development: A needs assessment for SDG monitoring and statistical capacity development. United Nations, New York, N.Y., USA.

European Data Protection Supervisor (EDPS). 2015. Meeting the challenges of big data: A call for transparency, user control, data protection by design and accountability. Opinion 7/2015.

European Environment Agency (EEA). 2017. Climate change, impacts and vulnerability in Europe 2016 — An indicator based report. EEA Report No. 1/2017. Publications Office of the European Union, Luxembourg, Luxembourg.

Fan, Y., Li, W., Gatebe, C.K., Jamet, C., Zibordi, G., Schroeder, T., and Stamnes, K. 2017. Atmospheric correction over coastal waters using multilayer neural networks. Remote Sens. Environ. **199**: 218–240. doi: 10.1016/j.rse.2017.07.016.

Fingas, M., and Brown, C. 2014. Review of oil spill remote sensing. Mar. Pollut. Bull. **83**(1): 9–23. doi: 10.1016/j.marpolbul.2014.03.059. PMID: 24759508.

Food and Agriculture Organization (FAO). 2018. The state of world fisheries and aquaculture 2018 — Meeting the sustainable development goals. FAO, Rome, Italy.

Gao, J. 2009. Bathymetric mapping by means of remote sensing: Methods, accuracy and limitations. Progress Phys. Geogr. **33**: 103–116. doi: 10.1177/0309133309105657.

Garrido, S., Silva, A., Marques, V., Figueiredo, I., Bryère, P., Mangin, A., and Santos, A. 2017. Temperature and food-mediated variability of European Atlantic sardine recruitment. Prog. Oceanogr. **159**: 267–275. doi: 10.1016/j.pocean.2017.10.006.

Gholizadeh, M.H., Melesse, A.M., and Reddi, L. 2016. A comprehensive review on water quality parameters estimation using remote sensing techniques. Sensors, **16**: 1298. doi: 10.3390/s16081298.

Giuliani, G., Lacroix, P., Guigoz, Y., Roncella, R., Bigagli, L., Santoro, M., et al. 2017. Bringing GEOSS services into practice: A capacity building resource on spatial data infrastructures (SDI). Trans. GIS, **21**: 811–824. doi: 10.1111/tgis.12209.

Group on Earth Observations (GEO). 2016. Group on Earth Observations Initiative 18: Earth observations in service of the 2030 Agenda for Sustainable Development, Strategic Implementation Plan 2016–2020. Available from http://eo4sdg.org/ [accessed 14 September 2018].

Halls, J., and Costin, K. 2016. Submerged and emergent land cover and bathymetric mapping of estuarine habitats using worldView-2 and LiDAR imagery. Remote Sens. **8**: 718. doi: 10.3390/rs8090718.

Hamylton, S.M., Hedley, J.D., and Beaman, R.J. 2015. Derivation of high-resolution bathymetry from multispectral satellite imagery: A comparison of empirical and optimisation methods through geographical error analysis. Remote Sens. **7**: 16257–16273. doi: 10.3390/rs71215829.

Hedley, J.D., Roelfsema, C., Brando, V., Giardino, C., Kutser, T., Phinn, S., et al. 2018. Coral reef applications of Sentinel-2: Coverage, characteristics, bathymetry and benthic mapping with comparison to Landsat 8. Remote Sens. Environ. **216**: 598–614. doi: 10.1016/j.rse.2018.07.014.

Henocque, Y., and Denis, J. (*Editors*). 2001. A methodological guide: Steps and tools towards integrated coastal area management. IOC Manuals and Guides No. 42. UNESCO, Paris, France.

Hollmann, R., Merchant, C.J., Saunders, R., Downy, C., Buchwitz, M., Cazenave, A., et al. 2013. The ESA Climate Change Initiative: Satellite data records for essential climate variables. Bull. Am. Meteorol. Soc. **94**: 1541–1552. doi: 10.1175/BAMS-D-11-00254.1.

Hossain, M.S., Bujang, J.S., Zakaria, M.H., and Hashim, M. 2015. The application of remote sensing to seagrass ecosystems: An overview and future research prospects. Int. J. Remote Sens. **36**: 61–114. doi: 10.1080/01431161.2014.990649.

Hu, C., Feng, L., Hardy, R.F., and Hochberg, E.J. 2015. Spectral and spatial requirements of remote measurements of pelagic *Sargassum* macroalgae. Remote Sens. Environ. **167**: 229–246. doi: 10.1016/j.rse.2015.05.022.

Huang, R., Yu, K., Wang, Y., Wang, J., Mu, L., and Wang, W. 2017. Bathymetry of the coral reefs of Weizhou Island based on multispectral satellite images. Remote Sens. **9**(7): 750. doi: 10.3390/rs9070750.

Intergovernmental Panel on Climate Change (IPCC). 2014. Climate Change 2014: Synthesis report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. *Edited by* R.K. Pachauri and L.A. Meyer. IPCC, Geneva, Switzerland.

International Council for Science (ICSU). 2017. A guide to SDG interactions: From science to implementation. *Edited by* D.J. Griggs, M. Nilsson, A. Stevance, and D. McCollum. International Council for Science, Paris, France.

Jackson, J.B.C. 2008. Ecological extinction and evolution in the brave new ocean. Proc. Natl. Acad. Sci. USA, **105**(Suppl. 1): 11458–11465. doi: 10.1073/pnas.0802812105. PMID: 18695220.

Jagalingam, P., Akshaya, B.J., and Hegde, A.V. 2015. Bathymetry mapping using Landsat 8 satellite imagery. Procedia Eng. **116**: 560–566. doi: 10.1016/j.proeng.2015.08.326.

Jin, X., Wah, B.W., Cheng, X., and Wang, Y. 2015. Significance and challenges of Big Data research. Big Data Res. **2**: 59–64. doi: 10.1016/j.bdr.2015.01.006.

Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., et al. 2016. A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. Remote Sens. **8**: 70. doi: 10.3390/rs8010070.

Kennedy, D.M., Ierodiaconou, D., and Schimel, A. 2014. Granitic coastal geomorphology: Applying integrated terrestrial and bathymetric LiDAR with multibeam sonar to examine coastal landscape evolution. Earth Surf. Processes Landforms, **39**(12): 1663–1674. doi: 10.1002/esp.3615.

Klemas, V. 2011. Remote sensing techniques for studying coastal ecosystems: An overview. J. Coastal Res. **27**(1): 2–17. doi: 10.2112/JCOASTRES-D-10-00103.1.

Klemas, V. 2014. Remote sensing of riparian and wetland buffers: An overview. J. Coastal Res. **30**(5): 869–880. doi: 10.2112/JCOASTRES-D-14-00013.1.

Klemas, V. 2015*a*. Remote sensing of floods and flood-prone areas: An overview. J. Coastal Res. **31**(4): 1005–1013. doi: 10.2112/JCOASTRES-D-14-00160.1.

Klemas, V. 2015*b*. Coastal and environmental remote sensing from unmanned aerial vehicles: An overview. J. Coastal Res. **31**(5): 1260–1267. doi: 10.2112/JCOASTRES-D-15-00005.1.

Kostylev, V.E., Courtney, R.C., Robert, G., and Todd, B.J. 2003. Stock evaluation of giant scallop (*Placopecten magellanicus*) using high-resolution acoustics for seabed mapping. Fish. Res. **60**(2–3): 479–492. doi: 10.1016/S0165-7836(02)00100-5.

Landsat Advisory Group (LAG). 2019. Landsat Advisory Group (LAG) status report. Landsat Science Team Meeting, 12 June 2019. Available from https://www.fgdc.gov/ngac/meetings/june-2019/landsat-advisory-group-report-ngac-jun-2019.pdf [accessed 27 August 2019].

Larnicol, M., Launeau, P., and Gernez, P. 2018. Using high-resolution airborne data to evaluate MERIS atmospheric correction and intra-pixel variability in nearshore turbid waters. Remote Sens. **10**(2): 274. doi: 10.3390/rs10020274.

Lejot, J., Delacourt, C., Piégay, H., Fournier, T., Trémélo, M.L., and Allemand, P. 2007. Very high spatial resolution imagery for channel bathymetry and topography from an unmanned mapping controlled platform. Earth Surf. Processes Landforms, **32**(11): 1705–1725. doi: 10.1002/esp.1595.

Lillesand, T.M., Kiefer, R.W., and Chipman, J.W. 2004. Remote sensing and image interpretation. 5th ed. Wiley, Hoboken, N.J., USA.

Liu, Q., Ruan, C., Zhong, S., Li, J., Yin, Z., and Lian, X. 2018. Risk assessment of storm surge disaster based on numerical models and remote sensing. Int. J. Appl. Earth Obs. Geoinf. **68**: 20–30. doi: 10.1016/j.jag.2018.01.016.

Long, N., Millescamps, B., Guillot, B., Pouget, F., and Bertin, X. 2016. Monitoring the topography of a dynamic tidal inlet using UAV imagery. Remote Sens. **8**(5): 387. doi: 10.3390/rs8050387.

Lundblad, E., Wright, D.J., Miller, J., Larkin, E.M., Rinehart, R., Naar, D.F., et al. 2006. A benthic terrain classification scheme for American Samoa. Mar. Geod. **29**(2): 89–111. doi: 10.1080/01490410600738021.

Lyons, M., Phinn, S., and Roelfsema, C. 2011. Integrating Quickbird multi-spectral satellite and field data: Mapping bathymetry, seagrass cover, seagrass species and change in Moreton Bay, Australia in 2004 and 2007. Remote Sens. **3**: 42–64. doi: 10.3390/rs3010042.

Madsen, K.S., Høyer, J.L., Fu, W., and Donlon, C. 2015. Blending of satellite and tide gauge sea level observations and its assimilation in a storm surge model of the North Sea and Baltic Sea. J. Geophys. Res.: Oceans, **120**(9): 6405–6418. doi: 10.1002/2015JC011070.

Maréchal, J.-P., Hellio, C., and Hu, C. 2017. A simple, fast, and reliable method to predict *Sargassum* washing ashore in the Lesser Antilles. Remote Sens. Appl.: Soc. Environ. **5**: 54–63. doi: 10.1016/j.rsase.2017.01.001.

Margarit, G., Barba Milanes, J.A., and Tabasco, A. 2009. Operational ship monitoring system based on synthetic aperture radar processing. Remote Sens. **1**(3): 375–392. doi: 10.3390/rs1030375.

Mélin, F., and Vantrepotte, V. 2015. How optically diverse is the coastal ocean? Remote Sens. Environ. **160**: 235–251. doi: 10.1016/j.rse.2015.01.023.

Mélin, F., Vantrepotte, V., Chuprin, A., Grant, M., Jackson, T., and Sathyendranath, S. 2017. Assessing the fitness-for-purpose of satellite multi-mission ocean color climate data records: A protocol applied to OC-CCI chlorophyll-*a* data. Remote Sens. Environ. **203**: 139–151. doi: 10.1016/j.rse.2017.03.039.

Mograne, M.A., Jamet, C., Loisel, H., Vantrepotte, V., Mériaux, X., and Cauvin, A. 2019. Evaluation of five atmospheric correction algorithms over French optically-complex waters for the Sentinel-3A OLCI Ocean Color Sensor. Remote Sens. **11**(6): 668. doi: 10.3390/rs11060668.

Monteys, X., Harris, P., Caloca, S., and Cahalane, C. 2015. Spatial prediction of coastal bathymetry based on multispectral satellite imagery and multibeam data. Remote Sens. **7**: 13782–13806. doi: 10.3390/rs71013782.

Moore, T.S., Campbell, J.W., and Feng, H. 2001. A fuzzy logic classification scheme for selecting and blending satellite ocean color algorithms. IEEE Trans. Geosci. Remote Sens. **39**(8): 1764–1776. doi: 10.1109/36.942555.

Moore, T.S., Campbell, J.W., and Dowell, M.D. 2009. A class-based approach to characterizing and mapping the uncertainty of the MODIS ocean chlorophyll product. Remote Sens. Environ. **113**: 2424–2430. doi: 10.1016/j.rse.2009.07.016.

Moore, T.S., Dowell, M.D., and Franz, B.A. 2012. Detection of coccolithophore blooms in ocean color satellite imagery: A generalized approach for use with multiple sensors. Remote Sens. Environ. **117**: 249–263. doi: 10.1016/j.rse.2011.10.001.

Moore, T.S., Dowell, M.D., Bradt, S., and Ruiz Verdu, A. 2014. An optical water type framework for selecting and blending retrievals from bio-optical algorithms in lakes and coastal waters. Remote Sens. Environ. **143**: 97–111. doi: 10.1016/j.rse.2013.11.021. PMID: 24839311.

Mouw, C.B., Greb, S., Aurin, D., DiGiacomo, P.M., Lee, Z., Twardowski, M., et al. 2015. Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. Remote Sens. Environ. **160**: 15–30. doi: 10.1016/j.rse.2015.02.001.

Myers, S.C., Gaffikin, L., Golden, C.D., Ostfeld, R.S., Redford, K.H., Ricketts, T.H., et al. 2013. Human health impacts of ecosystem alteration. Proc. Natl. Acad. Sci. USA, **110**(47): 18753–18760. doi: 10.1073/pnas.1218656110. PMID: 24218556.

NASA Ocean Color Web. 2019. Chlorophyll a (chlor_a). Available from https://oceancolor.gsfc.nasa.gov/atbd/chlor_a/ [accessed 30 August 2019].

National Geospatial Advisory Committee (NGAC). 2012. Landsat Advisory Group statement on landsat data use and charges, 18 September. Available from https://www.fgdc.gov/ngac/meetings/september-2012/ngac-landsat-cost-recovery-paper-FINAL.pdf [accessed 23 May 2019].

Nativi, S., Mazzetti, P., Santoro, M., Papeschi, F., Craglia, M., and Ochiai, O. 2015. Big data challenges in building the Global Earth Observation System of systems. Environ. Model. Softw. **68**: 1–26. doi: 10.1016/j.envsoft.2015.01.017.

Neumann, B., Ott, K., and Kenchington, R. 2017. Strong sustainability in coastal areas: A conceptual interpretation of SDG 14. Sustainability Sci. **12**: 1019–1035. doi: 10.1007/s11625-017-0472-y. PMID: 30147766.

Nicholls, R.J., and Cazanave, A. 2010. Sea-level rise and its impact on coastal zones. Science, **328**: 1517–1520. doi: 10.1126/science.1185782. PMID: 20558707.

Odermatt, D., Gitelson, A., Brando, V.E., and Schaepman, M. 2012. Review of constituent retrieval in optically deep and complex waters from satellite imagery. Remote Sens. Environ. **118**: 116–126. doi: 10.1016/j.rse.2011.11.013.

Ongley, E.D. 1996. Control of water pollution from agriculture. FAO Irrigation and Drainage Paper 55. Food and Agriculture Organisation of the United Nations, Rome, Italy.

O'Reilly, J.E., Maritorena, S., Mitchell, B.G., Siege, D.A., Carder, K.L., Garver, S.A., et al. 1998. Ocean color chlorophyll algorithms for SeaWiFS. J. Geophys. Res.: Oceans, **103**: 24937–24953. doi: 10.1029/98JC02160.

O'Reilly, J.E., Maritorena, S., Siegel, D.A., O'Brien, M.C., Toole, D., Mitchell, B.G. et al. 2000. SeaWiFS postlaunch calibration and validation analyses, Part 3. NASA Technical Memorandum 2000-206892. Vol. 11. *Edited by* S.B. Hooker and E.R. Firestone. NASA Goddard Space Flight Center, Greenbelt, Md., USA.

Ouellette, W., and Getine, W. 2016. Remote sensing for Marine Spatial Planning and Integrated Coastal Areas Management: Achievements, challenges, opportunities and future prospects. Remote Sens. Appl.: Soc. Environ. **4**: 138–157. doi: 10.1016/j.rsase.2016.07.003.

Pacheco, A., Horta, J., Loureiro, C., and Ferreira, Ó. 2015. Retrieval of nearshore bathymetry from Landsat 8 images: A tool for coastal monitoring in shallow waters. Remote Sens. Environ. **159**: 102–116. doi: 10.1016/j.rse.2014.12.004.

Paterson, S.K., Robin, D., Whyte, H., Le Tissier, M., and Scarrott, R. 2018. Supporting blue growth and risk management through earth observation. #EOCaribbean2018. EODAT Project: ESA SoW ref EOPS-EOEP-SW-00007. University College Cork, Ringaskiddy, Ireland.

Pelling, M., and Blackburn, S. (*Editors*). 2014. Megacities and the coast: Risk, resilience and transformation. Routledge, London, UK.

Plag, H.-P. (*Editor*), and the Workshop Participants. 2018. Workshop report "Implementing and Monitoring the Sustainable Development Goals in the Caribbean: The Role of the Ocean", Saint Vincent, Caribbean, 17–19 January 2018. GEOSS Science and Technology Stakeholder Network (GSTSN). Available from http://www.gstss.org/2018_Ocean_SDGs [accessed 17 October 2018].

Popescu, D., Ichim, L., and Stoican, F. 2017. Unmanned aerial vehicle systems for remote estimation of flooded areas based on complex image processing. Sensors, **17**(3): 446. doi: 10.3390/s17030446.

Rodriguez, J., Beard, T., Jr., Agard, J., Bennett, E., Cork, S., Cumming, G.S. et al. 2005. Interactions among ecosystem services. *In* Ecosystems and human well-being: Scenarios. *Edited by* S.R. Carpenter, P.L. Pingali, E.M. Bennett, and M.B. Zurek. Island Press, Washington, D.C., USA. pp. 431–448.

Rojas, C., Munizaga, J., Rojas, O., Martinez, C., and Pino, J. 2019. Urban development versus wetland loss in a coastal Latin American city: Lessons for sustainable land use planning. Land Use Policy, **80**: 47–56. doi: 10.1016/j.landusepol.2018.09.036.

Rumson, A.G., Hallett, S.H., and Brewer, T.R. 2017. Coastal risk adaptation: The potential role of accessible geospatial Big Data. Mar. Policy, **83**: 100–110. doi: 10.1016/j.marpol.2017.05.032.

Scarrott, R., Paterson, S., Tuohy, E., and Cronin, A. 2018. Utilising earth observation to support blue growth and risk management in the Caribbean: Workshop report. #EOCaribbean2018. EODAT Project: ESA SoW ref EOPS-EOEP-SW-00007. University College Cork, Ringaskiddy, Ireland.

Schaeffer, B.A., Schaeffer, K.G., Keith, D., Lunetta, R.S., Conmy, R., and Gould, R.W. 2013. Barriers to adopting satellite remote sensing for water quality management. Int. J. Remote Sens. **34**(21): 7534–7544. doi: 10.1080/01431161.2013.823524.

Spalding, M.D., Ruffo, S., Lacambra, C., Meliane, I., Hale, L.Z., Shepard, C.C., and Beck, M.W. 2014. The role of ecosystems in coastal protection: Adapting to climate change and coastal hazards. Ocean Coastal Manage. **90**: 50–57. doi: 10.1016/j.ocecoaman.2013.09.007.

Spalding, M.D., Burke, L., Wood, S.A., Ashpole, J., Hutchison, J., and Zu Ermgassen, P. 2017. Mapping the global value and distribution of coral reef tourism. Mar. Policy, **82**: 104–113. doi: 10.1016/j.marpol.2017.05.014.

Spyrakos, E., O'Donnell, R., Hunter, P.D., Miller, C., Scott, M., Simis, S.G.H., et al. 2018. Optical types of inland and coastal waters. Limnol. Oceanogr. **63**: 846–870. doi: 10.1002/lno.10674.

Staples, D., Brainard, R., Capezzuoli, S., Funge-Smith, S., Grose, C., Heenan, A. et al. 2014. Essential EAFM. Ecosystem approach to fisheries management training course. Volume 3 — Course presentations. FAO Regional Office for Asia and the Pacific, Bangkok, Thailand.

Steinmetz, F., Deschamps, P.-Y., and Ramon, D. 2011. Atmospheric correction in presence of sun glint: Application to MERIS. Opt. Express, **19**: 9783–9800. doi: 10.1364/OE.19.009783. PMID: 21643235.

Tebaldi, C., Strauss, B.H., and Zervas, C.E. 2012. Modelling sea level rise impacts on storm surges along US coasts. Environ. Res. Lett. **7**: 014032. doi: 10.1088/1748-9326/7/1/014032.

Traganos, D., Poursanidis, D., Aggarwal, B., Chrysoulakis, N., and Reinartz, P. 2018. Estimating satellite-derived bathymetry (SDB) with the google earth engine and Sentinel-2. Remote Sens. **10**(6): 859. doi: 10.3390/rs10060859.

Trochta, J.T., Mouw, C.B., and Moore, T.S. 2015. Remote sensing of physical cycles in Lake Superior using a spatio-temporal analysis of optical water typologies. Remote Sens. Environ. **171**: 149–161. doi: 10.1016/j.rse.2015.10.008.

UN Environment. 2018. Using satellite-based Earth observations to monitor SDG 6 indicators. Pilot study. NASA — University of Maryland. Available from http://eo4sdg.org/earthobservations-for-sdg6monitoring/ [accessed 20 September 2018].

UNISDR. 2015. Sendai framework for disaster risk reduction 2015–2030. *In* Outcome document of the Third United Nations World Conference on Disaster Risk Reduction in Sendai, Japan, 18 March 2015. pp. 12–39.

United Nations. 2015. Transforming our world: The 2030 agenda for sustainable development (A/RES/70/1). Available from https://sustainabledevelopment.un.org/post2015/transformingourworld/publication [accessed 26 October 2018].

United Nations. 2018. Global indicator framework adopted by the General Assembly (A/RES/71/313) and annual refinements contained in E/CN.3/2018/2 (Annex II), Maryland, USA. Available from https://unstats.un.org/sdgs/indicators/indicators-list/ [accessed 26 October 2018].

Van Son, S., Lindenbergh, R., de Schipper, M., de Vries, S., and Duijnmayer, K. 2009. Using a personal watercraft for monitoring bathymetric changes at storm scale. *In* Proceedings of Hydro '09, Cape Town, South Africa, 10–12 November 2009.

Vanderstraete, T., Goossens, R., and Ghabour, T.K. 2003. Remote sensing as a tool for bathymetric mapping of coral reefs in the Red Sea (Hurghada — Egypt). Belgeo, **3**: 257–268. doi: 10.4000/belgeo.16652.

Vanhove, M.P.M., Rochette, A.-J., and Janssens de Bisthoven, L. 2017. Joining science and policy in capacity development for monitoring progress towards the Aichi Biodiversity Targets in the global South. Ecol. Indic. **73**: 694–697. doi: 10.1016/j.ecolind.2016.10.028.

Vignudelli, S., Cipollini, P., Roblou, L., Lyard, F., Gasparini, G.P., Manzella, G., and Astraldi, M. 2005. Improved satellite altimetry in coastal systems: Case study of the Corsica Channel (Mediterranean Sea). Geophys. Res. Lett. **32**(7): L07608. doi: 10.1029/2005GL022602.

Vignudelli, S., Kostianoy, A.G., Cipollini, P., and Benveniste, J. (*Editors*). 2011. Coastal altimetry. Springer, Berlin, Germany.

Visbeck, M., Kronfeld-Goharani, U., Neumann, B., Rickels, W., Schmidt, J., van Doorn, E., et al. 2014. Securing blue wealth: The need for a special sustainable development goal for the ocean and coasts. Mar. Policy, **48**: 184–191. doi: 10.1016/j.marpol.2014.03.005.

von Maurich, O., and Golkar, A. 2018. Data authentication, integrity and confidentiality mechanisms for federated satellite systems. Acta Astronaut. **149**: 61–76. doi: 10.1016/j.actaastro.2018.05.003.

Wang, M., and Hu, C. 2017. Predicting *Sargassum* blooms in the Caribbean Sea from MODIS observations. Geophys. Res. Lett. **44**: 3265–3273. doi: 10.1002/2017GL072932.

Wang, M., and Hu, C. 2018. On the continuity of quantifying floating algae of the Central West Atlantic between MODIS and VIIRS. Int. J. Remote Sens. **39**(12): 3852–3869. doi: 10.1080/01431161.2018.1447161.

Wang, M., Hu, C., Cannizzaro, J., English, D., Han, X., Naar, D., et al. 2018. Remote sensing of *Sargassum* biomass, nutrients, and pigments. Geophys. Res. Lett. **45**: 12359–12367. doi: 10.1029/2018GL078858.

Webster, R.K., and Linton, T. 2013. Development and implementation of *Sargassum* Early Advisory System (SEAS). Shore Beach, **81**(3): 1–6.

Wells, R.J., and Rooker, J.R. 2004. Spatial and temporal patterns of habitat use by fishes associated with *Sargassum* mats in the northwestern Gulf of Mexico. Bull. Mar. Sci. **74**(1): 81–99.

Wheeler, B.W., White, M., Stahl-Timmins, W., and Depledge, M.H. 2012. Does living in the coast improve health and wellbeing? Health Place, **18**(5): 1198–1201. doi: 10.1016/j.healthplace.2012.06.015.

Wilson, M., O'Connell, B., Brown, C., Guinan, J., and Grehan, A. 2007. Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. Mar. Geod. **30**(1): 3–35. doi: 10.1080/01490410701295962.

World Meteorological Organization (WMO). 2016. The global observing system for climate: Implementation needs. GCOS Report No. 200. Available from https://gcos.wmo.int/en/gcos-implementation-plan [accessed 26 October 2018].

Wu, W., Yang, Z., Tian, B., Huang, Y., Zhou, Y., and Zhang, T. 2018. Impacts of coastal reclamation on wetlands: Loss, resilience and sustainable management. Estuarine, Coastal Shelf Sci. **210**: 153–161. doi: 10.1016/j.ecss.2018.06.013.

Zhang, L., Li, G., Zhang, C., Yue, H., and Liao, X. 2018. Approach and practice: Integrating Earth observation resources for data sharing in China GEOSS. Int. J. Digit. Earth. doi: 10.1080/17538947.2018.1504995.

Zhang, M., Hu, C., Cannizzaro, J., English, D., Barnes, B.B., Carlson, P., and Yarbro, L. 2018. Comparison of two atmospheric correction approaches applied to MODIS measurements over North American Waters. Remote Sens. Environ. **216**: 442–455. doi: 10.1016/j.rse.2018.07.012.

Zheng, G., and DiGiacomo, P.M. 2017. Uncertainties and applications of satellite-derived coastal water quality products. Prog. Oceanogr. **159**: 45–72. doi: 10.1016/j.pocean.2017.08.007.