APP4SEA
Seabird vulnerability & marine oil spill risks, a remote sensing approach

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APP4SEA

ARCTIC PREPAREDNESS PLATFORM

FOR OIL SPILL AND OTHER ENVIRONMENTAL ACCIDENTS

Seabird vulnerability and marine oil spill risks, a remote sensing approach

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Northern Periphery and Arctic Programme 2014–2020

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The 21st century brought unprecedented interest in the Arctic resources, turning the region from the world's unknown periphery into the center of global attention.

Within the next 50 years, local coastal communities, their habitual environment and traditional lifestyle will undergo severe changes, starting from climatic perturbations and ending with petroleum industrial intervention and increased shipping presence.

The APP4SEA project, financed by the Northern Periphery and Arctic Programme will contribute to environmental protection of the Arctic waters and saving the habitual lifestyle of the local communities. It will improve oil spill preparedness of local authorities and public awareness about potential oil tanker accidents at sea.

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Abbreviations

ADM-Aeolus	Atmospheric Dynamics Mission Aeolus
AIS	Automatic identification System
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CALIPSO	Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation
CCMP	Cross-Calibrated Multi-Platform
CDS	Climate Data Store
Chl	Chlorophyll
DNB	Day/Night Band
DWH	Deepwater Horizon
ECMWF	European Centre for Medium-Range Weather Forecasts
EMODnet	European Marine Observation and Data Network
EO	Earth observation
ERA5	ECMWF Reanalysis 5th Generation
EuroBIS	European Ocean Biogeographic Information System
ESR	Earth Space Research
FNMOC	Fleet Numerical Meteorology and Oceanography Center
GBIF	Global Biodiversity Information Facility
GEBCO	General Bathymetric Chart of the Oceans
GHRSST	Group for High Resolution Sea Surface Temperature
H	Horizontal (polarization)
HYCOM	HYbrid Coordinate Ocean Model
LIF	Laser induced fluorescence
LWIR	Long-wave infrared (wavelengths, 8–14 µm)
MODIS	Moderate Resolution Imaging Spectroradiometer
MWIR	Medium-wave infrared (wavelengths, 3–5 µm)
NASA	National Aeronautics and Space Administration

NCEP	National Centers for Environmental Prediction
NIR	Near infrared (wavelengths, 750-1400 nm)
NOAA	National Oceanic and Atmospheric Administration
OBIS	Ocean Biogeographic Information System
OSCAR	Ocean Surface Current Analysis Real-time
PODAAC	Physical Oceanography Active Archive Centre
RCM	RADARSAT Constellation Mission
R-CNN	Region-based Convolutional Neural Network
RGB	Red, Green and Blue
SAR	Synthetic aperture radar
SMAP	Soil Moisture Active Passive
SMOS	Surface Moisture Ocean Salinity
SNPP	Suomi National Polar-orbiting Partnership
SOTO	State Of The Ocean
SSH(A)	Sea surface height (anomaly)
SSS	Sea surface temperature
SST	Sea surface salinity
SWH	Significant wave height
SWIR	Short wave infrared (wavelengths, 1.1-3 μm)
TIR	Thermal infrared (wavelengths, 3-14μm)
U	Eastward component of vector
UAV	unmanned aerial vehicle
USGS	U.S. Geological Survey
UV	Ultraviolet (wavelengths, 10-400 nm)
V	Northward component of vector, or vertical (polarization)
VIIRS	Visible-Infrared Imager-Radiometer Suite
VIS	Visible (wavelengths, 400-750 nm)
YOLO	You Only Look Once

1. Introduction

1.1. Background

Several review papers have described the potential of remote sensing for conservation and biodiversity studies (e.g., Gillespie et al., 2008; Pettorelli et al., 2014; Rose et al., 2014; Turner et al., 2003). A review of Wang et al. (2010) focuses on the instruments and techniques of state-of-the-art spaceborne remote sensing. Rose *et al.* (2014), in collaboration with remote sensing scientists and conservation organizations, identifies 10 questions in conservation that remotely sensed data could greatly help answer. They list questions such as, how remote sensing can improve the modelling of species distributions and abundances, the understanding of animal movements, and the prediction of ecosystem response and resilience to multiple stressors. Near real-time (operational) Earth observation (EO) systems could support rapid response to ecosystem threats such as catastrophic oil spills at sea. The spatial and temporal resolutions are usually coarser than the resolutions at which many taxa interact with their environment (Rose et al., 2014). However, the space industry is progressing fast and with the developments of new products and higher resolutions the range of EO data is ever increasing. We focus on satellite remote sensing, as these data are usually readily available, mostly free and sometimes for sale, but we also present some other helpful EO data sets.

The field of remote sensing for conservation and biodiversity studies as described in the review papers is quite extensive and applies to a wide range of research questions. However, they all agree that both communities (remote sensing and ecology / biodiversity) need to integrate and collaborate across disciplines to realize its potential. This current study is an attempt to do that by addressing the question how remote sensing can support the estimation of oil spill risk to seabirds. There are two general approaches to remote sensing of biodiversity (Turner *et al.*, 2013). One is direct remote sensing of individual organisms, colonies, or rafts, which has been effective for penguins and albatrosses (Fretwell et al., 2012; 2014; 2017). The other indirect remote sensing of biodiversity through reliance on environmental parameters as proxies. In relation to seabirds, one could think of for example sea surface temperature (SST) and salinity (SSS) as those proxies (Haney, 1989; Durant *et al.*, 2014). SSS and SST are routine EO data. The same is true for the remote sensing of oil spills. We can directly detect large oil spills from space, an example is the oil spill caused by the explosion on the Deepwater Horizon oilrig April 20, 2010 (Leifer *et al.*, 2012). Small oil spills, such as from boat engines, are too small to track from space and will have to be estimated from their correlation with ship tracks, urbanization, and other proxies. We will organize the following sections accordingly: (2) direct remote sensing of seabirds, (3) indirect remote sensing of seabirds, (4) direct remote sensing of oil spills, (5) indirect remote sensing of oil spills, and (6) summary and conclusion.

We aim to estimate seabird distribution at sea as here is where they are vulnerable to oil spills. Outside the breeding season, seabirds spend most of their time at sea. During the breeding season they breed on land and forage at sea. Seabirds may be easier to sense on land than in water if they breed at a relatively small number of sites and breed out in the open on a background where they have high contrast with their surrounding environment (Fretwell et al., 2012; 2017). If they breed in colonies it may be possible to observe a colony from space (Fretwell et al., 2012). Most seabird colonies are observed on or near the coast where remote sensing estimations of seabirds can be verified with relative ease.

1.2. Seabirds

Remote sensing of wild animals is most successful if we know where to look (Fretwell et al., 2012; 2017; Guirado et al., 2019). Seabirds are not tied to a central place except during the breeding season when the distance between the breeding grounds on land and the feeding zones at sea is a major constraint. Northern seabirds usually forage within 200 km but many seabirds regularly traverse hundreds or thousands of kilometres during foraging trips (Durant et al., 2004), while the flight range of kittiwakes (*Rissa tridactyla*) is up to 80 km from the colony (Garthe, 1997). Garthe (1997) found virtually no black-headed gull (*Larus ridibundus*), sandwich tern (*Sterna sandvicensis*) and common/arctic terns (S. hirundo/paradisaea) at distances over 25 km from the nearest colony but no clear relationship for lesser black-backed gulls and guillemots. Thaxter et al. (2012) provide estimates of foraging ranges for 25 species of UK breeding seabirds ranging from 9 km (red-throated diver, *Gavia stellata*) to 400 km (northern fulmar, *Fulmarus glacialis*). In summary, it depends on the bird species how far from the breeding site we need to remote sense the sea surface for their presence. Before each remote sensing plan, we need to gather as much further information as possible for each seabird species (table 1).

Table 1. Key information required for each seabird species for direct and indirect remote sensing

Seabird Species		Direct	Indirect
Individual size		x	
Colouring		x	
Body surface temperature		x	
Breeding season	period	x	x
	location	x	x
	in colony / size of colony	x	
	nests (burrowed or open)	x	
Non-breeding season	period	x	x
	location	x	x
	in raft or solo	x	
Feeding biology	planktivorous or piscivorous		x
	fishing ship follower or not		x
	foraging range	x	x
	depth below the sea surface		x
Flying characteristics	flight mode		x
	flight range	x	x

EuroBIS (European Ocean Biogeographic Information System) makes their previous seabird observation data (among other marine species) available through different portals [r1]. The OBIS (Ocean Biogeographic Information System) and GBIF (Global Biodiversity Information Facility) data portals on this site give access to global data.

1.3. Oil spills

Oil spills caused by catastrophes with oil tankers and production platforms get a lot of attention, making the general public aware of them. However, a large oil spill that occurs over the deep ocean in open water where few birds reside has a lesser effect on seabirds than a small spill in at a location with high numbers of birds on the water surface (TRB NRC, 2003).

Chronic low-level contamination from washing out tanks and dumping bilge water and other oily waste represents a danger at least three times higher than that of catastrophic accidents with oil tankers (Oceana, 2005). Close to one oiled seabird per kilometre of coast has been estimated for Atlantic waters of Canada, similar to an estimate for the German and Belgian coasts of the North Sea (Oceana, 2005). In 90% of cases on Canada and various European coasts, evidence has been found that the oil polluting seabirds relates to ships' bilge water. Other surprising sources of oil spill contamination that are small but numerous are recreational vessels and surface water runoff (TRB NRC, 2003). For mapping seabird vulnerability to marine oil spill risks, we therefore investigate remote sensing of large oil spills, as well as of the smaller diffuse sources.

1.4. Remote sensing

In this paper we will refer to data and tools that are publicly available, most at no cost (after registration) and some for a fee. The links (referred to as "r##") are listed in Table 2. We do not aim to give a non-exhaustive list of all datasets and tools but instead refer to those that seem most useful. We will focus on EO data of Level 3 (geophysical variables mapped on a uniform space-time grid) and higher. We therefore include reanalysis data, which are model data combined with satellite and in situ observations to estimate an ocean variable (Level 4). Sometimes only Level 2 and/or 1 are available. Level 1 means instrument data have been obtained and geocoded, and Level 2 that geophysical variables have been derived at the same resolution and location as they were obtained, but not yet mapped on a uniform grid. Thus, we must find the swaths that coincide with our region and time of interest. Details of the datasets referred to in the text, such as parameters, coverage and resolution, are presented in Table 3.

EO data come in different formats and a useful tool to plot geo-referenced and other arrays from netCDF, HDF, GRIB, he5, and other datasets is Panoply, offered by the National Aeronautics and Space Administration (NASA) [r2]. In Panoply, the user can export the data in the formats CDL (text file including metadata and data), CSV (spreadsheet), and Labelled Text (tab delimited file). Another useful tool by NASA is State Of The Ocean (SOTO), an interactive web-based tool to search for and visualize a broad range of satellite-derived ocean observations [r3].

We will refer to a range of EO climate and sea surface data made available through NASA's Physical Oceanography Active Archive Centre (PODAAC) [r9]. We will also use Copernicus, the European Union's EO Programme that provides data at their Climate Data Store (CDS) [r16], and other EO data sources (r4, r7, r21, and r25). We also suggest datasets that are not based on satellite remote sensing but that have useful data (r1, r26, r27, and r28). We refer to data with the highest resolutions, but sometimes lower resolutions are more convenient as they can be easier to work with. Lower resolutions are often available from the same source.

Table 2. Hyperlinks to tools and databases in the text. Last accessed 28 January 2020. Ctrl + Click to follow link.

r1	eurobis.org/data_access_services
r2	giss.nasa.gov/tools/panoply
r3	podaac-tools.jpl.nasa.gov/soto
r4	scihub.copernicus.eu/dhus/#/home
r5	step.esa.int/main/toolboxes/snap/
r6	earthexplorer.usgs.gov
r7	satimagingcorp.com/satellite-sensors/worldview-3
r8	tensorflow.org
r9	podaac.jpl.nasa.gov/
r10	dataset/MUR-JPL-L4-GLOB-v4.1
r11	dataset/SMAP_RSS_L3_SSS_SMI_8DAY-RUNNINGMEAN_V4
r12	dataset/JASON_3_L2_OST_OGDR_GPS
r13	dataset/ALTIKA_SARAL_L2_OST_XOGDR
r14	dataset/OSCAR_L4_OC_third-deg
r15	dataset/SEA_SURFACE_HEIGHT_ALT_GRIDS_L4_2SATS_5DAY_6THDEG_V_JPL1812
r16	cds.climate.copernicus.eu/
r17	cdsapp#!/dataset/reanalysis-era5-single-levels
r18	cdsapp#!/dataset/reanalysis-era5-pressure-levels
r19	cdsapp#!/dataset/satellite-sea-level-global
r20	cdsapp#!/dataset/reanalysis-era5-land
r21	oceancolor.gsfc.nasa.gov/
r22	l3
r23	cgi/browse.pl?sen=am
r24	esr.org/research/oscar
r25	ncdc.noaa.gov/data-access/model-data/model-datasets/navoceano-hycom-glb
r26	download.gebco.net
r27	marinetraffic.com
r28	emodnet-humanactivities.eu/
r29	view-data.php
r30	search.php
r31	earthobservatory.nasa.gov/features/NightLights
r32	worldview.earthdata.nasa.gov
r33	worldmap.harvard.edu/maps/6718/e2v
r34	remss.com

Table 3. Database details (Table 2)

					Resolution			
link	Source	Data	Start date	Coverage	Spatial	Temporal	Latency	Level
r1	EuroBIS	Seabird sightings data	1900	Global	NA	NA	NA	NA
r4	Copernicus	Sentinel-2, imaging	Jun 2015	56° S - 84° N	10 m × 10 m	5 day	1 day	2
r7	WorldView-3	Commercial satellite imagery	Aug 2014	Global	0.31 m × 0.31 m	<1 day		3
r10	PODAAC	SST foundation, sea ice	Jun 2001	Global	0.01° × 0.01°	1 day	hours	4
r11	PODAAC	SSS	Apr 2015	Global	0.25° × 0.25°	8 day	72 hours	3
r12	PODAAC	SWH	Sep 2016	66° S - 66° N	11.2 km × 5.1 km	10 day	5 hours	2
r13	PODAAC	SWH	Dec 2013	88° S - 88° N	11 km × 5 km	35 day	9 hours	2
r14	PODAAC	Surface currents	Nov 1992	66° S - 66° N	0.33° × 0.33°	5 day	120 hours	4
r15	PODAAC	SSH, SSHA	Oct 1992	Global	0.17° × 0.17°	5 day	hours	4
r17	CDS	ERA5 surface - atmosphere	Jan 1979	Global	0.25° × 0.25°	1 hour	5 days	4
r17	CDS	ERA5 surface - ocean waves	Jan 1979	Global	0. 5° × 0.5°	1 hour	5 days	4
r18	CDS	ERA5 on 37 pressure levels	Jan 1979	Global	0.25° × 0.25°	1 hour	1 month	4
r19	CDS	Surface currents, SSH, SSHA	Jan 1993	Global	0.25° × 0.25°	1 day	6 months	4
r20	CDS	Snow cover over land	Jan 1981	Global	0.1° × 0.1°	1 hour	6 months	4
r22	NASA OC	Chl, Kd490	Jul 2002	Seasonal	4 km × 4 km	1 day	2 weeks	3
r23	NASA OC	MODIA Aqua (swaths)	Jul 2002	Global	1 km × 1 km	2 day	1 day	2
r25	HYCOM	Surface currents	Mar 2013	Global	0.08° × 0.08°	3 hours	0[1)]	4
r26	GEBCO	Bathymetry	Na	Global	0.004°× 0.004°	NA	NA	grid
r27	MarineTraffic	Ship tracking / vessel density	2009	Global	NA	NA	0	NA
r28	EMODnet	Human activities and more	2017/2018	Europe	NA	NA	1 year	NA

1) 4-day forecast

2. Direct remote sensing of seabirds

2.1. Spectral imaging in optical spectrum

Turner et al. (2003) mention multispectral sensors that can resolve objects at spatial scales small enough to resolve species and species assemblages. Technology has advanced since then and we expect multispectral imaging capable of observing individual birds, groups of birds, or bird communities directly if the resolution on the ground is high enough, i.e., an image pixel covers a small enough area on the ground. Direct remote sensing of wild animals is at present only practical if we zoom in on an area where we expect them to see, based on previous studies (Fretwell et al., 2012; 2017), low resolution images (Guirado et al., 2019) or indirect remote sensing (section 3). Multispectral imaging is a passive remote sensing technique, passive because it measures reflectance of natural daylight and does not supply its own light (or other power) source, and multispectral because it measures light at certain wavelengths (colours) in corresponding spectral bands. Visible wavelengths (VIS) range from about 400 to 750 nm, while near infrared (NIR) ranges from 750 to 1400 nm. Spectral bands can be narrow-band, wide-band or cover the whole spectrum (panchromatic). Of recent, or soon-to-launch, EO satellite missions capable of ocean colour observations, the Sentinel-2, provides the finest spatial resolution at no cost to the user (Table 6 in Werdell, et al., 2018). The multispectral sensor, MSI, on board Sentinel-2 has a spatial resolution of 10 m × 10 m for three bands in VIS (blue, green and red) and one in NIR. The revisit time is 5 days, which results in 2-3 days at mid-latitudes due to overlap between swaths from adjacent orbits. A limitation of remote sensing in the optical spectrum is, is that it is only possible during daylight hours, which can be very short in the Arctic (Antarctic) during winter (summer) and can be obscured by clouds and overcast skies. Level 2 data are freely and fully available through Copernicus Open Access Hub [r4] or the more user friendly United States Geological Survey (USGS) Earth Explorer [r6]. A Sentinel-2 toolbox to visualise, analyse and process optical high-resolution products from Sentinel-2 is freely available. It also provides support for third party data from EO satellites such as SPOT and MODIS (Aqua and Terra), Landsat (TM) and others. The toolbox is part of the Sentinel Application Platform (SNAP) [r5].

We can only detect birds in VIS if they have a contrasting colour to the background. Seabird feathers are not brightly coloured, being white, black, grey or a combination to blend in with the sea surface. The plumage of some seabird species (e.g., gulls) changes with sex, age, and season. A white back shows up better against a dark background such as the sea. A dark back is easier to see against a bright background, for example snow and ice in the Polar Regions. PODAAC offers 0.01° × 0.01° sea ice fraction data from June 2001 [r10], while CDS has made available their dataset containing hourly snow coverage over land on a 0.1° × 0.1° grid from 1981 [r20]. A better method could be using the NIR band, especially to spot birds flying over- or resting on the sea surface, as water absorbs most NIR light.

A limitation using satellite imagery (both in VIS and NIR) is image resolution. In a 10 m × 10 m resolution image, one image pixel represents a 10 m × 10 m area on the ground. Using this resolution, we cannot not recognize individuals with body sizes smaller than 10 m × 10 m , which is significantly larger than any seabird, which varies from the Little Auk (Wingspan: 36-39 cm) to the Wandering Albatross (Wingspan: 2.51 to 3.5 m). At 10 m resolution satellite imagery, Fretwell et al. (2012) identify colonies with at least 200 emperor penguins (*Aptenodytes fosteri*) in the snow. Species like emperor penguins are suitable for remote sensing because they breed at a relatively small number of sites and they breed mainly on sea ice where they have high contrast with their surrounding environment as their feathers of the head and back are black (Fretwell et al., 2012). Fretwell et al. (2012) used QuickBird imagery of the identified colonies with a resolution of 61 cm in the panchromatic band (450-900 nm), in which individual Emperor penguins show as a single, or multiple pixels. When penguins group into close clusters, which happens most of the time, they cannot differentiate between individuals, however Fretwell et al. (2017) use 31 cm resolution colour imagery from the WorldView-3 (WV-3) satellite to count individuals of the wandering albatross (*Diomedea exulans*) and the closely related northern royal albatross (*Diomedea sanfordi*) on their nests. (WV-3's panchromatic sensor (450 - 800 nm) captures an image at a resolution of 31 cm, used to sharpen the blue, green and red recordings at 1.24 m resolution). The albatrosses are evident as white dots in this satellite imagery. We note that the emperor penguin is the largest of the living penguins and the wandering albatross one of the largest living birds in the world. According to Fretwell et al. (2017), the minimum detectable body size is two pixels (62 cm for WV-3). Seabird colonies are easier to see than individual seabirds but not all species breed in colonies everywhere. It varies from single pairs (i.e. great-black backed gulls) to colonies of millions of pairs (i.e. little auks) and is location dependant.

WV-3, QuickBird and other imagery and data are for sale at the Satellite Imaging Corporation [r7]. In 2008, Gillespie et al. (2008) reported a price of US$3000–5000 for 10 km^2 high-resolution imagery with the expectation that cost should decrease with competition and an increasing number of archived images. The highest available resolution at that time was 0.6 m (Gillespie et al., 2008) and the price has indeed decreased considerably. More than 10 years later, the minimum order requirement for archived high-resolution satellite imagery, with a pixel resolution of 0.5 m is 25 km^2 or US $ 312.50 (about 3% of the 2008 price) and higher for new collection and 30 cm resolution satellite imagery, depending on product type. Both Sentinel-2 and WV-3 are placed in sun-synchronous orbit, meaning they always fly over a location on Earth at the same time of day. In conclusion, spectral imaging of individual birds is possible at present, if we know where and when we are looking, but the resolution is too low to separate between species.

2.2. Thermal infrared imaging

Thermal infrared (TIR) imaging cameras are widely used to observe and detect wild animals and their habitats, and to estimate their population size (Cilulko et al., 2013). Two types of TIR cameras operate in different atmospheric windows of the TIR spectrum: medium-wave infrared (MWIR) at 3–5 µm, and long-wave infrared (LWIR) at 8–14 µm. Thermal imaging does not need the sun or any other external power source. It measures the thermal radiance coming from a surface, as well as the thermal radiance of the surroundings reflected off that surface. The TIR signal is a combination of the temperatures of surface and surroundings, and their emissivity values. (Emissivity is the ratio of the energy radiated from a surface, and that radiated from a black body; the higher emissivity the stronger thermal radiance). The lower the emissivity of a surface, the higher its reflectivity. Thermal imaging is therefore not only dependent on the thermal differential of the animal or heat radiating from an active nest to ambient temperature (Boonstra et al., 1995), but also on the emissivity values of the background and the bird's body surface. Emissivity of most animal coats range between 0.94 and 1.0, likely altered by water and dirt (McCafferty et al., 2011), the same range as for seawater, ice and snow (Kuenzer and Dech, 2003). This would imply that we can only differentiate animals with a coat from a water surface or on snow surface if their body temperature is different (Goddijn-Murphy and Williamsson, 2019). The body temperature of most birds varies around 40±3 °C (Willmer et al., 2004), which is higher than SST anywhere in the world and tens of degrees higher than in temperate coastal waters (Willmer et al., 2004). According to McCafferty et al. (2011), infrared thermal imaging represents the temperature of the plumage several millimetres below the outer surface. A wind speed as light as 1 m s^{-1} can cool this temperature by a couple of degrees, while sunlight can warm a plumage, especially when it is a dark colour (McCafferty et al., 2011). In addition, evaporation of water on a wet plumage can cool. The air temperature naturally also plays a role. Varying environmental conditions will therefore make it difficult to generalize the TIR signal of the seabirds and apply TIR sensing on a large scale. Objects that appear with the same brightness as seabirds, for example oceanic whitecaps, will make it even more difficult. High-spatial resolution satellite TIR sensors currently in orbit are TIRS (TIR Sensor) on board Landsat 8 (30 m resolution) and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) on board Terra (90 m resolution). These spatial resolutions are much coarser than those that operate in the optical spectrum, and we conclude that for monitoring species and species assemblages, direct TIR imaging from space is at present not suitable. However, TIR sensing of SST has proven to be useful for indirect remote sensing seabird habitats (Haney, 1989). ASTER and Landsat data are freely available through USGS Earth Explorer [r6].

2.3. Image recognition

Birds in images can be counted manually by human observers (e.g. Fretwell et al., 2012;2017) or automatically using digital image processing techniques. Automated image recognition techniques are capable of processing large data sets. The methods shown to be most successful in detecting birds distributed across various environments are those that involve machine-learning and more recently, deep-learning. Deep-learning is a subfield of machine learning whereby features can be learned from given data by themselves, whereas existing machine-learning techniques require a feature selection process. The performance of deep-learning based methods for wild bird detection has been demonstrated to be higher than that of machine-learning based methods (Hong et al., 2019). Hong et al. (2019) assess various deep-learning methods using aerial photographs collected by an unmanned aerial vehicle (UAV). The size of one bird in each aerial photograph is 40 × 40 pixels for a 1.5 cm × 1.5 cm resolution. Their methods should be applicable to satellite observations if the resolution on the ground is the same or better. Hong et al. (2019) find that Faster R-CNN (Region-based Convolutional Neural Network) (Ren et al., 2015) to be most accurate and YOLO (You Only Look Once) (Redmon et al., 2016) to be fastest. Guirado et al. (2019) apply Faster R-CNN in a two-step approach, the first step to find Google Earth images where whales are present and the second step to count whales in those images. In detecting 30 m large whales, pixel sizes of 2.5 m and smaller are successful. According to Guirado et al. (2019), a pixel size under 1 m would be required for detecting cetaceans shorter than 5 m. We deduce that for recognizing a 0.5 m large bird in the sea, we would need a pixel size of at least 0.1 m. This is at present too ambitious but may be possible in the future. Guirado et al. (2019) use open-source tools for their CNN-based image processing: Google TensorFlow deep-learning framework (Huang et al., 2016) and Google TensorFlow Object Detection API (Abadi, et al., 2016) for respective step-1 and step-2. This open source machine learning platform is available through [r8]. Faster R-CNN and YOLO are also available in the programming language Matlab® if its toolboxes “machine learning and deep learning” and “image processing and computer vision” are installed. Fretwell et al. (2012;2017), Guirado et al. (2019) and Hong et al. (2019) use RGB (red, green and blue) images but the image processing methods would not necessarily be limited to those kinds of images. They could also be applied to images in the NIR, SWIR (short wave infrared) and even TIR.

3. Indirect remote sensing of seabirds

3.1. Proxies for seabird presence

Direct remote sensing of seabirds is only possible if we have an idea of when and where they are present. To detect them at sea, where they are at greater risk to oil spills , can be difficult. Indirect remote sensing of seabirds will not enable us to count individual birds, but it may help us exclude certain areas or indicate where the birds are more likely to be seen than others. According to Haney et al. (1989), geographic variables such as distance from land and water depth alone do not explain seabird distributions and are less precise than habitats defined by sea surface conditions. He gives examples of physical and biological habitat characters retrievable from satellite remote sensing such as, SST, SSS and density, ocean colour and chlorophyll (Chl), and dynamic topography. This was three decades ago and since then, satellite remote sensing of the sea surface has progressed in a major way. More and increasingly precise measurements are now routinely obtained at higher temporal and spatial resolutions. Stuart et al. (2011) recommend habitat mapping of marine species using their basic relationships with their oceanic environment and satellite derived Chl and SST data. We could then apply direct remote sensing to obtain more detail. Possible proxies routinely measured using remote sensing are: SST (sea surface temperature), SSS, air temperature, wind, and location of fronts and currents (Durant et al., 2004; Haney, 1989), Chl concentration (Suryan et al., 2012), water depth (Garthe, 1997), turbidity (Henkel, 2006) and trawler abundance (Garthe, 1997). These parameters relate to these species directly through physiological effects or indirectly through an influence on prey availability (Durant et al., 2004). Seabirds species that feed well below the sea surface correspond less with sea surface characteristics, and hence their distribution may be less well explained by remote sensing, than that of species that are restricted to the ocean surface (Haney, 1989). We will confine to those variables that relate to the distribution of seabirds directly, and not indirectly for example through their influence on factors like laying date, breeding success and mortality. The relations between proxies and seabird distribution are clearly different for different seabird species (e.g., Durant et al., 2004; Garthe, 1997).

3.1.1. Sea surface temperature (SST)

Changes in SST affect different species in different ways depending upon the birds' feeding biology. Warm sea temperatures tend to decrease the plankton productivity but may increase fish growth. Planktivorous species are therefore more likely correlated with low SST while piscivorous species with high SST (Durant et al., 2004). More than absolute temperatures, the pattern of sea surface isotherms (lines of equal temperature) are commonly used as indicators of marine habitats (Haney, 1989). Haney (1989) characterizes the habitats of the black-capped petrel (*Pterodroma hasitata*) in the Gulf Stream using TIR satellite images. SST observations can also help us find convergent oceanic fronts where prey species concentrate (Section 3.1.8).

EO data

SST has a complex vertical temperature structure in the upper ocean (~10 m) that can change during the day as the sun heats the upper water layer. Remote sensed SST signifies the skin or subskin of the sea surface and SST at depth is derived from an assimilation with *in situ* instruments. SST at a range of depths is available from several platforms.

The European Centre for Medium-Range Weather Forecasts (ECMWF) produces reanalysis climate datasets such as ERA5 (ECMWF Reanalysis 5th Generation). ERA5 at a single level records contain global, hourly estimates of variables from 1979 to present [r17]. The variable SST therein represents the average temperature of the uppermost metre of the ocean on a 0.25°× 0.25° grid; it therefore exhibits diurnal variations. At a higher spatial resolution (0.05°× 0.05°) but lower temporal resolution, daily SST foundation data are made available by PODAAC, for example those produced by the Group for High Resolution Sea Surface Temperature (GHRSST) [r10]. The estimates are composed from several instruments including TIR radiometers, microwave radiometers, and in situ SST observations. Foundation SST is SST at 10 m depth, where diurnal effects are absent. The coverage is global with a time span from 2002-Jun-01 to present. This dataset also contains sea ice fraction data.

3.1.2. Air temperature

The air temperature generally fluctuates much more than SST and during very hot or very cold air temperatures and seabirds may respond by remaining in contact with seawater to reducing the cost of thermoregulation (Durant et al., 2004).

EO data

Aforementioned ERA5 reanalysis not only also produces global hourly air temperature data at 2 m height, but also on 37 pressure levels (from 1000 hPa to 1 hPa) from 1979 to present, on a 0.25°× 0.25° grid [r18].

3.1.3. Sea surface salinity (SSS)

SSS in the south-eastern North Sea corresponds with seabird density in different ways for different species. Northern fulmar (*Fulmarus glacialis*) and common guillemots (*Uria aalge*) increase, while black-Headed gull (*Chroicocephalus ridibundus*), common gull (*Larus canus*), herring gull (*Larus argentatus*), common tern (*Sterna hirundo*) and arctic tern (*Sterna paradisaea*) decrease, with increasing SSS (Garthe, 1997). This may be related to their diets. As with SST, SSS can point to converging fronts, for example between river input and receiving seawater (Section 3.1.8).

EO data

Only two satellite sensors have been launched to specifically study SSS. These are NASA's Soil Moisture Active Passive (SMAP) and ESA's Surface Moisture Ocean Salinity (SMOS) passive microwave sensors. Passive microwave sensors are radiometers that operate at the same wavelengths as those used for TIR imaging but are non-imaging. The former provides 8-day SSS data on a 0.25° × 0.25° grid from April 2015 [r11]. These records also contain sea ice area fraction and land area fraction.

3.1.4. Sea ice

Sea ice is linked to foraging for species which are associated with sea ice, for example penguins in the southern Hemisphere and ivory gulls (*Pagophila eburnea*) in the northern Hemisphere. Emperor penguins rely on sea-ice as a breeding platform (Fretwell et al., 2014).

EO data

Fretwell et al. (2014) use ENVISAT synthetic aperture radar imagery of sea-ice concentration several times over the course of the breeding season to assess why a colony location of Emperor penguins had moved from sea-ice to ice-shelf. PODAAC (CDS) offers 0.01°×0.01° (0.25°×0.25°) sea ice fraction data from June 2001 (from 1979) [r10] ([r17]).

3.1.5. Wind

The foraging energetics of different seabird species likely depends on wind speed and direction in different ways. According to Durant et al. (2004), birds relying on flapping (e.g., species such as black-legged kittiwake, *Rissa tridactyla*, and the little auk, *Alle alle)*, will use more energy when the wind is strong, whereas the effect will be the opposite for gliding species (e.g., the northern fulmar). Amorim et al. (2008) find significant relations between wind components and seabird distribution. They imply that an increase in wind-generated water turbulence leads to enhanced phytoplankton. Wind blowing over the sea will increase sea surface roughness, i.e., create waves and oceanic whitecaps. Oceanic whitecaps, which appear for wind speeds higher than 3-4 m s^{-1} (Goddijn-Murphy et al., 2011), can be easily mistaken for seabirds on the sea surface. We discuss the presence of waves in the next section 3.1.6.

EO data

Passive microwave sensors and active microwave sensors such as the scatterometer, synthetic aperture radar, and radar altimeter, have been measuring wind speed over the sea surface for decades. These usually estimate wind speed at 10 m height above the sea surface from sensing sea surface roughness. If the *U* (eastward) and *V* (northward) wind speed components are given, they can be combined to give the speed and direction of the horizontal wind. ERA5 on a single level [r17] contains global, hourly estimates of 10 m and 100 m wind speed (*U* and *V*) from 1979 to present on a 0.25° × 0.25° grid. ERA5 on 37 pressure levels [r18] gives wind speed for a range of heights (see Section 3.2.3.) as well as wind parameters such as vertical velocity (air motion in the upward or downward direction) and vorticity (measure of the rotation of air in the horizontal). Another source of freely available Level-3 wind field data is Remote Sensing Systems [r34], who offer cross-calibrated multi-platform (CCMP) gridded surface vector winds using satellite, moored buoy, and model wind data. They produce four global maps per day on 0.25° × 0.25° grid.

3.1.6. Ocean waves

The wind creates local wind waves, after which the waves begin to propagate away from the source while they organise themselves into lines of swell. Swell waves can travel for thousands of kilometres away from their source. A relation between ocean waves and seabird behaviour is to be expected as sea surface roughness would affect their ability to feed and rest on the surface. Also, large breaking waves and oceanic white capping will make it more difficult to directly remote sense birds. Either way, we will need to assess sea surface roughness when remote sensing seabirds at sea.

EO data

PODAAC offers Level-2 significant wave height (SWH) data derived from JASON-3 satellite at a spatial resolution of 11.2 km x 5.1 km with a repeat time of 10 days [r12]. The coverage is from 66°S to 66°N. They also present Level-2 significant SWH data from the SARAL / ALTIKA altimeter of a similar spatial resolution on a larger coverage (88°S to 88°N) but longer repeat time (35-day) [r13]. A range of hourly wave parameters on a 0.5° × 0.5° grid (e.g., SWH, period and direction for wind, swell and total swell waves) are available from ERA5 [r17].

3.1.7. Chlorophyll concentration

Chl concentration has been used to link primary productivity and seabird distributions in the marine environment through remotely sensed Chl a (e.g., Haney, 1989; Garthe, 1997; Amorim et al. 2008; Suryan et al., 2012). Suryan et al. (2012) find that satellite derived peak Chl *a*, and not simply average Chl *a* concentration, is a robust predictor of seabird distributions in the California Current System.

EO data

Satellite ocean colour sensors have been used to estimate Chl a for decades (Werdell et al., 2018). Suryan et al. (2012) uses monthly Level-3 chl *a* concentration at (9 km × 9 km) resolution from SeaWiFS to identify seabird hotspots; SeaWiFS stopped operating in December 2010. NASA's OceanColor Web [r21] distributes ocean-related products from a large number of operational, satellite-based remote-sensing missions providing ocean colour, SST and SSS data to the international research community. Data include current gridded Chl concentration from the (Moderate Resolution Imaging Spectroradiometer) MODIS-aqua and its successor (Visible-Infrared Imager-Radiometer Suite - Suomi National Polar-orbiting Partnership) VIIRS-SNPP at 4 km × 4 km and 9 km × 9 km resolution for daily and longer periods [r22]. The daily data do not cover the whole globe as data from companion sensor MODIS-Terra are not recommended for ocean colour observations (Groom et al, 2019). Because the local solar time of MODIS-aqua's fly-over is in the afternoon, during winter (summer) months there is no daylight for observations at latitude over (under) approximately 45° north (south), while during the spring (autumn) there are no data above (below) the arctic (Antarctic) circle. Level 2 data, the data before gridding, have a higher spatial resolution (1 km) and matching swaths for MODIS and other sensors be searched [r23].

3.1.8. Currents, sea surface height and the location of fronts

Oceanographic features such as fronts and currents may concentrate prey species and provide an anticipated food supply for seabirds. For example, Antarctic and sub-Antarctic seabirds are closely linked to the polar front and sub-Antarctic front (Durant et al., 2004). In the North Atlantic, several frontal systems within the Irish Sea and North Sea have been linked to predictable resources for seabirds (Durant et al., 2004). Amorim et al. (2008) define productivity fronts as discontinuity areas of lower SST and higher Chl *a* than their adjacent areas. The variation in sea surface height (SSH) associated with changes in horizontal circulation are a more direct physical analog to marine habitats than SST, SSS, and density, ocean colour and Chl (Haney, 1989). Tidal currents, that occur in concurrence with the rise and fall of the tide, flow in addition to large-scale surface ocean currents. Birds frequently visit energetic tidal-stream environments, attracted by their enhanced prey abundance, vulnerability and diversity (Benjamins et al., 2015). The association with specific tidal phases, current strengths and flow structures can be different for different seabird species. Cooper et al (2015) finds that the tidal flows and direction are consistent with tracks of razorbills (*Alca torda*) while they are resting on the sea overnight and drifting with the tidal flows.

O data

Currents

OSCAR (Ocean Surface Current Analysis Real-time), an assimilation product generated by Earth Space Research (ESR) [r24], contains near-surface ocean current estimates of *U* and *V* (averaged over the top 30m of the ocean) on a 0.33° × 0.33° grid with a 5-day resolution. Data are available through PODAAC [r14]. Copernicus' CDS provides daily geostrophic current data on a 0.25° × 0.25° grid on [r19].

Sea surface height

Sea surface height anomalies (SSHA) above a mean sea surface on a 1/6th degree grid (0.17° × 0.17°) for a 5-day period are available from PODAAC [r15]. Copernicus provides daily SSHA and absolute dynamic topography data on a 0.25° × 0.25° grid on [r19].

Fronts

We can recognize ocean fronts between different water bodies, and other physical ocean properties, from their SST and SSS signals. We can also use an ocean colour signal because the biological signal in the ocean colour data can be a proxy for the structure and motion of the water (Shutler et al., 2006). Examples are the green colour indicating high Chl concentrations that may identify regions of nutrient rich upwelling water, and the yellow colour of coastal river plumes containing dissolved organic matter contrasting with the bluer receiving seawater.

Tides

Tidal current and sea elevation data are not resolved by above products, for these we need satellite data assimilated with in situ and model data. The Fleet Numerical Meteorology and Oceanography Center (FNMOC) provides HYbrid Coordinate Ocean Model (HYCOM) output for free. HYCOM produces daily global 3-hourly snapshots of the ocean at 1/12º resolution from March 2013 of tidal currents (*U* and *V*) as well as sea elevation, SSS and SST at 40 depth levels from 0-5000 m. The National Centers for Environmental Prediction (NCEP) provides HYCOM output on a global (regional) scale for the surface [r25]. Some ocean fronts are tidal, for example those separating river plume and coastal waters.

3.1.9. Water depth and distance to the coast

All seabirds are obviously constrained by their maximum flight range, which can vary with species from tens to thousands of kilometres (e.g., Garthe, 1997; Durant et al., 2004). The distance from the coast also varies depending on whether they are coastal or pelagic foragers. Different seabird species can dive to different depths, from gulls and terns who can access prey in the top 1 m to penguins such as the king penguin (*Aptenodytes patagonicus*) which can dive to 100–300 m. Garthe (1997) identifies a land–sea gradient, including variables such as distance to land/nearest colony, water transparency, water depth, etc., as the most important factor in seabird sightings in the North Sea. It is difficult to separate water depth from the other variables as low (high) water depth, low (high) transparency, low (high) SSS all correspond with low (high) distance to the coast. The seabird species were somewhat separated with regards to the land-sea gradient, with the Northern Fulmar and Common Guillemot clearly more present further out to sea than the other species while the Black-headed Gull, Sandwich Tern and Common/Arctic Terns were virtually absent at distances from the nearest colony over 25 km (Garthe 1997). Month, wind, distance to shore and/or tern colonies, and distance to seamounts mainly explain variability in abundance of shearwaters and terns in the Azores (Amorim et al., 2008).

EO data

Land-sea mask and model bathymetry data on a 0.25° grid are included in ERA5 [r17] but this grid is too coarse to resolve all small islands and bays. The General Bathymetric Chart of the Oceans (GEBCO) provides publicly-available bathymetry data (height above mean sea level) of the world's oceans on a much higher resolution, 15”×15”, grid [r26].

3.1.10. Turbidity

Turbidity inversely relates to water clarity and, as with water depth above, correlates with other variables in the land-sea gradient because coastal waters are usually more turbid than seawater further out to sea. Turbidity may also correlate with Chl when it is caused by dissolved organic matter. High clarity is possibly associated with high concentrations of zooplankton and small fish which are the major prey of northern fulmar and common guillemot (Garthe, 1997). According to Henkel (2006), forster's terns (*Sterna forsteri*) occurred more frequently than expected over turbid water and brandt's cormorants (*Phalacrocorax penicillatus*) over clear waters, while some seabirds use marine habitats with a wide range of water clarities.

EO data

Water clarity is commonly quantified by the diffuse attenuation coefficient, K_d, at 490 nm (visible light in the blue to green region of the spectrum) of sub surface downwelling light in the aquatic environment. For example, a K_d(490) of 0.1 m^{-1} means that light intensity reduces one natural log within 10 meters of water while for a K_d(490) of 0.5 m^{-1} this happens over 5 meters. Thus, higher K_d(490) values mean lower clarity of ocean. K_d(490) data records are in the same data sets as those mentioned for Chl above and hence retrievable from [r22] (Level 3) and [r23] (Level 2).

3.1.11. Trawler abundance

The great black-backed gull, black-headed gull, and herring gull are increasingly present near fishing trawlers as they consume discards. No ship-followers at all were found in sandwich terns, common/Arctic terns, or guillemots (Garthe, 1997).

EO data

Ship tracks have been observed from satellites from anomalous cloud lines over the ocean for more than half a century (Conover, 1966) but it has not been possible to differentiate by ship type. This kind of information is provided by MarineTraffic [r27]. They offer global live maps and vessel density data for 2016/2017 using vessels' automatic identification system (AIS) for free, but historical data (since 2009) come at a cost. The human activities portal of European Marine Observation and Data Network (EMODnet) [r28] shows a range of human activities such as vessel density data for 2017/2018 and route density for 2019 in Europe [r29] and these data can be downloaded for free [r30]. Both MarineTraffic and EMODnet data can be selected by ship type, such as fishing.

3.2. Summary

It has become clear that there is not one single remote sensing approach applicable to all seabird species due to their different features, habitats and relations with their environment. For each seabird species we need the information listed in Table 1 before developing a remote sensing plan. Regarding direct remote sensing, commercial images give superior spatial / temporal resolution (0.31 m × 0.31 m / < 1 day) [r7]. Sentinel-2 offers the highest resolution for freely available images (10 m × 10 m / 5 day) [r4]. Regarding indirect remote sensing, CDS [r16] offers the highest temporal resolution data (hourly) for many ocean surface and atmosphere data while PODAAC [r10] offers a higher spatial resolution for SST and sea ice but on a daily basis. All datasets contain more than one variable, for example additional land-sea mask, but these may not be the best available. GEBCO [r26] presents superior resolution bathymetry data, while HYCOM [r25] superior current data.

4. Direct remote sensing of oil spills

Direct remote sensing is applicable to large oil spills floating on the sea surface. Examples are, the Deepwater Horizon (DWH) spill in the U.S. Gulf that began on April 20, 2010 (Leifer et al., 2012), leaking oil platforms in the Caspian Sea (Fingas and Brown, 2017), and oil spills trailing ships (Alpers, et al., 2017). Remote sensing of these oil spills is achieved using different techniques, for reviews we refer the reader to Leifer et al (2012) and Fingas and Brown (2014), and more recent, Fingas and Brown (2017). Passive remote sensing in the form of imaging in the ultraviolet (UV) to VIS to NIR spectrum is common because of availability and low cost. It measures the optical properties of oil and water: higher reflectance of oil compared to water and for some sensors the polarization of light reflected by oil. However, clouds and sun glint can impair the images and they can only be taken during daylight hours. Oil has no specific spectral features in the UV-NIR spectrum that would allow for separating its signal from many possible background signals. Imaging in LWIR uses the thermal and emissive properties of oil and water and does not need a light source, and sun glint is absent. In both visible and thermal images, natural objects in the sea such as ocean fronts, sediments and organic matter may seem like oil. An active sensor is the light detection and ranging (lidar) sensor, which emits laser light (light at one wavelength) and measures backscatter. Because the laser pulse can penetrate the water surface and measure back scatterers in the water column, it can also measure submerged oil. Leifer et al. (2012) found some evidence of submerged oil near the DWH site in post-spill CALIPSO (Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation) data. A special kind of lidar uses laser induced fluorescence (LIF), based on oil molecules absorbing UV light energy and re-emitting it as visible light. LIF is capable of differentiating between different kinds of oil, such as marine diesel and crude oil (Raimondi et al., 2017). LIF can detect oil on the shore and discriminate between oiled and unoiled seaweeds (Fingas and Brown, 2018), and could therefore be useful in detecting oiled birds. Commercial instruments are available, and development of the technology continues. Satellite-borne lidars that are capable of detecting oil have other priorities. CALIPSO is primarily a cloud aerosol profiler and ESA's Atmospheric Dynamics Mission Aeolus (ADM-Aeolus) a wind profiler. LIF lidars are currently not in space and only used in in situ and airborne sensing.

Radar is now the standard for mapping offshore oil as it can cover large-areas, and also at night-time and through clouds and fog (Leifer et al., 2012; Fingas and Brown, 2017; Alpers et al., 2017). The radar emits a microwave and measures the back scatter reflected by the sea surface. It thus images the small-scale sea surface roughness produced by capillary waves, short ocean waves with wavelengths in the order of centimeters. Because oil on the water surface dampens waves, it reduces the small-scale sea surface roughness and an oil spill will look dark in a radar image. Passive microwave sensing and LWIR imaging have been used to estimate the thickness of oil slicks (Fingas and Brown, 2017). Limitations of radar imaging of oil spills are that surfactants (man-made and natural) and other look-alikes occur on the water surface (Section 5.2) and that it only works for wind speeds between 1.5 and 10 m/s. Below there is not enough texture to the water surface and above wind waves are too high. The position and shape of the dark areas need to be interpreted to distinguish mineral oil spills from look-alikes. Alpers et al. (2017) show examples of mineral spills at sea, (1) a dark line trailing a ship visible as a bright spot, (2) a dark linear feature broadening from one end to the other, and (3) a dark feathered shape patch. They also show examples of look-alikes. We cannot use radar to identify an oil covered bird because oil spills are monitored by measuring the smoothness of the sea surface, and not using an inherent property of the oil.

For satellite-borne radars, the radar configuration is synthetic aperture radar (SAR) (Finglas and Brown, 2017). SAR operates at different wavelengths, some state that the X-band performs best for oil spill detection (Leifer et al., 2012; Finglas and Brown, 2017), while others favour the L-band (Alpers et al, 2017). Most spaceborne SAR data are acquired in C- or X-band. The polarization of the radar wave, which signifies horizontal (H) or vertical (V) propagation of both transmission and reception, is also important. If transmission and reception are polarized vertical (horizontal) it is denoted by VV (HH) and is called single polarization; it can also be cross-polarized, VH and HV, quadrupole (all four poles are used), or mixed. According to Alpers et al. (2017), single-polarization SAR works best for oils spill detection as it is less sensitive to instrument noise. Finglas and Brown (2017) present a list of satellite borne SAR sensors. We list a few that are currently in orbit in Table 4. Swath width and resolution for one satellite range widely as these vary with image acquisition modes, such as Stripmap, Interferometric Wide swath, Extra-Wide swath, and Wave for Sentinel-1, or SpotLight, StripMap and ScanSAR for TerraSAR-X/Tandem-X. The revisit time (not to be confused with repeat time which indicates the satellite completing a whole cycle) depends on the latitude of the location and is between one- and four-days (it decreases going North). Some satellite radars operate in a constellation: TerraSAR-X is twinned with Tandem-X and Sentinel-1 and RCM respectively consist of two and three satellites, while Cosmo Skymed consists of four. Adding satellites lowers the revisit time. Oil pollution monitoring at 50 m resolution is 3-4 days or daily (on average) for Radarsat-2 and the RADARSAT Constellation Mission (RCM) respectively. SAR images are generally processed in near real-time (times of 4 hr are possible), making them useful for operational oil spill monitoring.

There are currently only low-level SAR products available and the user has to process the SAR images themselves. This involves the following steps (Finglas and Brown, 2017). (1) Quality assessment of the image. (2) Removal of speckle and noise. (3) Removal of wind fields and fixed geographic features (e.g., land, shallow areas or weed beds). (4) Edge detection to locate the oil “dark” spots. In the past 10 years, artificial intelligence (AI) systems have been developed to automate image processing for oil detection in radar images. ESA’s open source SNAP contains a Sentinel-1 toolbox for processing, reading and writing, displaying and analysing SAR images [r5]. It also works for SAR images from TerraSAR-X/Tandem-X, COSMO-SkyMed, RADARSAT-2 and others. The toolbox has tools for calibration, speckle filtering, co-registration, orthorectification, mosaicking, data conversion, polarimetry and interferometry, and basic routines for oil spill detection. Gancheva and Peneva (2019) have verified the SNAP tool for oil spill detection in the Bulgarian Black Sea. For the data processing they use a virtual machine with 4 core processors and 32 GB memory. They find that automatic oil spill detection is only successful for large oil spills away from the shoreline, and that an additional classification procedure (not in SNAP) or visual inspection by a human operator is required for verification of the results.

Satellite SAR images of the highest resolution are commercial (top 4 rows in Table 4), the cost varying with image acquisition mode (e.g., resolution, size and polarization). For example, one RADARSAT-2 scene can cost from 3,600 to 7,800 $CAD with optional additional costs for higher levels of processing. Cosmo Skymed lists standard prices from €825 to €6000 depending on acquisition mode and date (images >30 days old are half the price of new images). Acquisition for each scene needs to be specified and planned with commercial data providers. Sentinel-1 data are global and freely available [r4], while the general public can view certain images of tRCM). Those wishing to view further RCM image products, will be able to apply to become vetted users in early 2020 by going through a security screening process.

Table 4. Non-exhaustive list of satellites carrying SAR sensors currently in orbit; launch date refers to latest satellite in the constellation; Resol. is resolution; ʎ indicates the radar wavelength.

Satellite	Launch date	Resol. (m)	Swath (km)	ʎ	SAR data source
RADARSAT-2	2007	1-100	18-500	C	mdacorporation.com/geospatial/international
TerraSAR-X*	2010	0.25-40	4 -270	X	intelligence-airbusds.com/optical-and-radar-data
Cosmo Skymed	2010	1-100	10-200	X	e-geos.it/#
Kompsat-5	2013	0.85-20	5-100	X	si-imaging.com
Sentinel-1	2013	5-40	20-400	C	sentinels.copernicus.eu/web/sentinel/missions; [r4]
RCM	2019	3-100	20-500	C	asc-csa.gc.ca/eng/satellites/radarsat/default.asp

**) In constellation with Tandem-X*

In summary, satellite remote sensing of oil spills is in development and oil spill maps are not readily available. SAR imagery from Sentinel-1 is free, but the user needs to process these using the open source toolbox. Time and memory resources may be a limitation (Gancheva and Peneva, 2019). Ancillary information that helps identify genuine mineral oil spills and disqualify look-alikes will improve oil spill detection. Alpers et al. (2017) list information such as, Chl distribution indicating biological slicks; location of oil platforms, terminals and seeps; the sea surface current field and wind field; location of sandbanks; the location of current fronts; the air-sea temperature difference (a dark area indicates a negative value related to decreased sea surface roughness); rain distribution; and ship traffic data. It is not possible to detect oiled birds at sea or on shore from satellites, but oiled birds may be detectable using an airborne LIF sensor.

5. Indirect remote sensing of oil spills

Satellite remote sensing of oil spills using the freely available Sentinel-1 SAR data and SNAP processing software with oil spill detection routines is only viable for large, catastrophic oil spills away from the shore (Gancheva and Peneva, 2019). However, oil tanker or oil platform accidents do not pose the only risk. Nearly half of the pollution of European seawaters caused by crude oil, and other refined products results from international maritime traffic washing out tanks and dumping bilge water (Oceana, 2003). In U.S. marine waters, the largest spills come from vessels, followed by pipelines and facilities (TRB NRC, 2003). Other examples of small sources of oil pollutions are natural oil seeps, small vessels, and surface runoff water contaminated with oil. Small recreational vessels and land-based oil together account for account for nearly three quarters of the petroleum introduced to North American waters from activities associated with petroleum consumption (TRB NRC, 2003). Although these oil spills are by themselves too small and diffuse to be visible from space, their contribution to marine oil pollution is major. We therefore need to use oil spill proxies. These proxies can also improve the detection of large oil spills by identifying look-alikes and locating the areas at risk. The following sections describes these proxies and look-alikes and where to find EO data. We will refer back to previous sections because most available satellite and other EO data that are applicable have been discussed in the sections about direct and indirect remote sensing of seabirds.

5.1. Proxies of marine oil spills, large and small

5.1.1. Vessel density

International maritime traffic is a major cause of diffuse oil pollution by washing out tanks and dumping bilge water. It is therefore sensible to monitor marine traffic. Conover (1966) was the first to detect ship tracks in satellite images in the form of anomalous cloud lines. These days, ships can be viewed using SAR as a dark line following a bright spot in Alpers et al. (2017), VIIRS DNB (Lee et al., 2006), or any direct remote sensing method described in Section 2 if the boat is large enough. However, as explained in Section 3.1.11, the most complete and detailed information on international marine traffic is on MarineTraffic [r27] and EMODnet [r28]. Their vessel density maps indicate a risk to catastrophic accidents with oil carrying tankers, and to small diffuse sources of oil pollution discussed above (Section 5.1).

5.1.2. Harbours

Harbors suffer chronic contamination from a variety of sources. It may be derived from the burning of fossil fuels, accidental oil spills, and chronic inputs from nearby marine terminals, tank farms and wastewater disposal. Also, if oil is stranded in protected, low-energy environments such as bays and harbors, it can stay in the water for years. Harbors and marinas are therefore high-risk areas for seabirds regarding oil spill contamination. The location of ports and marinas are shown by MarineTraffic [r27] and main European ports by EMODnet [r28].

5.1.3. Oil platforms and pipelines

We can associate the location of oil platforms and pipelines with operational and accidental discharge of oil. These can be large, such as the DWH spill, the largest oil spill to ever occur in U.S. waters. Or they can be small and chronic, for example a leaking pipeline. Either way, they pose a risk to seabirds at sea. Knowing their sites can locate this risk and also help us separate real oil spill from look-alikes (Alpers et al., 2017). EMODnet [r28] presents the locations and details of oil and gas boreholes, offshore installations, and pipelines in European waters and data can be downloaded for free. On a global scale, we can consult the Oil & Gas Map of WorldMap [r33]. Data for the worlds's petroleum fields (onshore and offshore) shown in WorldMap are available through the link therein (Päivi et al., 2007). WorldMap also shows oil refineries.

5.1.4. Urban surface runoff water and recreational vessels

Most cars drip oil onto road and parking surfaces, usually on waterproof concrete or asphalt. This oil can build up on the ground, so that when there is rain or flooding, the oil washes into the ocean. The volume of oil naturally increases with both population density and the percent of paved surface near the coast, which can be linked to urbanization. Increasing urbanization also indicates increasing use two-stroke recreational vessels, of which gasoline and lube oil inputs are a surprisingly large marine source of petroleum hydrocarbons (TRB NRC, 2003). An example of urbanization visible from space is the nighttime view of the Earth from VIIRS Day/Night Band (DNB), showing the lights at night (Lee et al., 2006). Recent VIIRS images taken on board the joint NASA/NOAA (National Oceanic and Atmospheric Administration) SNPP satellite are available from NASA's Earth at Night [r31]. Another possibility is exploring MODIS/Terra + aqua yearly land cover type data on a global 500 m grid (latest year 2018). These land cover data, one type being urban and built-up lands, in HDF format are freely available from NASA's Worldview [r32]. (Worldview also shows Earth at Night, but data cannot be downloaded from here. ERA5 on a single level [r17] contains data of water runoff rates (surface, sub-surface, and total) which indicate drought or flood.

5.1.5. Currents, sea surface height and the location of fronts

D'Asaro et al (2018) show with surface drifter experiments that floating materials can concentrate at density fronts and that oil spills, for instance, could increase in thickness by a factor of 104 in convergence areas. Surface convergences can move with large internal waves generated by internal tides through their movement over banks, reefs, and the continental shelf break. These have been demonstrated to concentrate and transport larval invertebrates, fish and tar balls from an oil spill. The most common site for the generation of these internal waves is the continental shelf break (Van Sebille et al., 2020). Remote sensing of oceanographic features such as fronts and currents is discussed in Section 3.1.8.

5.2. Remote sensing of look-alikes

5.2.1. Oil from natural seeps

Natural processes are responsible for over 60 percent of the petroleum entering North American waters, and over 45 percent of the petroleum entering the marine environment worldwide (TRB NRC, 2003). Natural oil seeps are often near oil and gas exploration fields (TRB NRC, 2003). Even though the input from seeps is very large, ecological impacts appear to be limited in area, suggesting that the slow rate of release allows biota to acclimate to toxic releases (TRB NRC, 2003). Conclusion Kvenvolden and Cooper (2003) show a global locations map of naturally occurring crude-oil seeps that impact the marine environment. Hovland (1992) show location maps of hydrocarbon seeps in northern marine waters (defined as regions north of 45° N of Canada/Alaska and north of 55° N elsewhere).

5.2.2. Biogenic slicks

Biogenic slicks can cause similar changes to radar backscattering as mineral oil films, making the identification of mineral oil difficult. In SAR images, biogenic slicks display less variations because it consists of one molecular layer, as opposed to mineral oil films that can form multilayers on the sea surface with variable thickness (Alpers et al., 2017). Chl-a distribution is a likely proxy for the presence of biogenic slicks. Section 3.1.7 describes EO available remote sensing data of Chl concentration. However, biogenic films slicks persist on the sea surface for some time after periods of high biological activity, and they may also drift away from its point of origin due to the action of currents, winds, and waves (Alpers et al., 2017).

5.2.3. Cold surface water

The air-sea temperature difference affects small scale sea surface roughness, a negative value smooths the sea surface and reduces radar backscatter. This can cause cold upwelling water to look like an oil spill in a SAR image. ERA5 at a single level contains global, hourly estimates of water and air temperatures from 1979 to present on a 0.25°× 0.25° grid [r17]. For the remote sensing of SST, see Section 3.1.1.

5.2.4. Wind and rain

Raindrops falling on the water surface can both enhance and reduce radar backscatter relative to the background. Raindrops impacting the sea surface enhance radar backscatter by generating ring waves and splash products, while associated winds roughen the sea surface. At the same time, raindrops can reduce radar backscatter by damping the short surface waves, smoothing the sea surface (Alpers et al., 2016; 2017). It is therefore useful to know the rain distribution. ERA5 at a single level includes global, hourly estimates of rain rates averaged over the 0.25°× 0.25° model grid boxes [r17]. Remote Sensing Systems [r34] offer different rain rate products derived from passive microwave radiometers. Both ERA5 and Remote Sensing Systems' measurements include sea surface wind data (see Section 3.1.5).

5.2.5. Shallow sandbanks

Sandbanks appear dark on SAR images taken during ebb tide (Alpers et al., 2017). More on HYCOM [r25] tidal data can be found in Section 3.1.8 and on bathymetric maps from GEBCO [r26] in Section 3.1.9. This information is not sufficient to locate sandbanks as they can move around and change shape with moving water. Wang et al. (2019) use moderate resolution (10–100 m) images acquired by various satellites to monitor sandbanks during different tidal phases. See Section 2.1 for more about spectral imaging, for example by the freely available, current Sentinel-2 images on 10 m resolution and higher resolution, commercial alternative.

6. Summary and conclusion

We have described publicly available satellite remote sensing and other EO data for assessing the vulnerability of seabirds to oil spills. This obviously involves remote sensing of seabirds. We can use direct methods (high resolution imaging) and indirect methods using seabird proxies, and most effectively a combination of both. Many satellite data are freely available but the highest resolution images come at a cost. Remote sensing needs to be optimized for different species because relations between seabirds and their environment are species specific. In addition, we would like to know when and where to look, searching for seabirds over the whole globe at all times is not feasible to our knowledge. The latter also applies to oil spills large and small. Usually, large oil spills involving accidents with oil tankers and platforms (e.g., DWH) are reported, and remote sensing methods are used to evaluate the subsequent oil spill pollution (Leifer et al., 2012) and long-term impact on the environment (Mo et al., 2017). Small oil spills are too small and diffuse to be seen from space but their contribution to marine oil pollution is significant (TRB NRC, 2003). Satellite based sensors cannot identify oiled seabirds at sea yet, but an airborne LIF lidar possibly could. Commercial instruments are available, and development of the technology continues. In conclusion, there are two first approaches in using remote sensing to assess oil spill vulnerability of seabirds. These are to assess the presence of oil spills and seabirds at (1) known seabird habitats, or (2) sites of known oil pollution. The former should be concerning one seabird species, and the latter either caused by large accidental oil spills or diffuse small oil spills.

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APP4SEA is funded under the European Regional Development Fund (ERDF)

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