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Considerations for transferring an operational dynamic ocean management tool between ocean color products

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ABSTRACT

Satellite remote sensing data are critical for assessing ecosystem state and evaluating long-term trends and shifts in ecosystem components. Many operational tools rely on continuous streams of remote sensing data, and when a satellite sensor reaches the end of its designed lifespan, these tools must be transferred to a more reliable data stream. Transferring between data streams can produce discontinuities in tool products, and it is important to quantify these downstream impacts and understand the mechanisms that cause discontinuity. To illustrate the complexities of tool transfer, we compare five products for ocean chlorophyll-a, which is a proxy for phytoplankton biomass and an important input for tools that monitor marine biophysical processes. The five chlorophyll-a products included three blended products and two single sensor products from MODIS and VIIRS. We explored the downstream impacts of tool transfer using EcoCast: an operational dynamic ocean management tool that combines real-time predictions from target and bycatch species distribution models to produce integrated surfaces of fishing suitability. EcoCast was operationalized using MODIS chlorophyll-a, and we quantify the impacts of transferring to the intended replacement of MODIS, VIIRS, and test if impacts can be minimized by using a blended chlorophyll-a product instead. Differences between chlorophyll products did not linearly propagate through to the species model predictions and the integrated fishing suitability surfaces. Instead, differences in species model predictions were determined by the shape of chlorophyll-a response curves in the species models relative to chlorophyll-a differences between sensors. However, differences in the integrated fishing suitability surfaces were reduced by canceling of differences from individual species model predictions. Differences in the integrated fishing suitability surfaces were not reduced by transferring to a blended product, highlighting the complexity of transferring operational tools between different remote sensing data products. These results contribute to our general understanding of the mechanisms by which transferring between data streams impacts downstream products. To aid decision-making regarding tool transfer, we developed an interactive web application that allows end-users to explore differences in chlorophyll products within times period and regions of interest.

1. Introduction

Remote sensing data are critical for environmental management, and are commonly used for assessing current ecosystem state, evaluating long-term trends, and identifying shifts in ecosystem components. A myriad of operational tools such as ecological indicators, ecological forecasts, and natural disaster preparedness systems rely on near real-time streams of satellite remote sensing data to observe ecosystem state and change (Quayle et al., 2004; Anderson et al., 2016; Welch et al., 2019a). However, remote sensing instruments have finite life spans, requiring operational tools to transfer to new environmental data streams when sensor quality degrades. Switching data streams may introduce discontinuities in the downstream products generated by operational tools, challenging efforts to accurately monitor and predict ecosystem state (Beaulieu et al., 2013). To minimize the impacts of these discontinuities, the effects of transitioning between

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environmental data streams needs to be quantified and planned for before implementation.

Ocean chlorophyll-a estimates (hereafter chlorophyll), a proxy for phytoplankton biomass, are a critical input for tools that characterize and monitor marine biophysical processes such as upwelling, harmful algal blooms, and species movements. Satellite-borne sensors have monitored chlorophyll since the mid-1970s, beginning with the proof-of-concept Coastal Zone Color Scanner, followed by the Sea-viewing Wide Field-of-View Sensor (SeaWiFS), the Moderate-Resolution Imaging Spectroradiometers (MODIS), the MEdium Resolution Imaging Spectrometer (MERIS), the Geostationary Ocean Color Imager (GOCI), the Visible Infrared Imager Radiometer Suite (VIIRS), and most recently the Ocean and Land Colour Instrument (OLCI) launched in 2016. In addition, several blended products have been developed that integrate chlorophyll estimates from multiple sensors, such as those produced by GlobColour and ESA Ocean Color Climate Change Initiative (Hollmann et al., 2013; ACRI-ST GlobColour Team, 2017). These blended products were developed to minimize known temporal discontinuities (Garnesson et al., 2019; Gregg and Casey, 2010; Uprety et al., 2013) and spatial biases (Belo Couto et al., 2016; Djavidnia et al., 2010; Nuris et al., 2017) among chlorophyll sensors.

Since its launch aboard the Aqua satellite in 2002, the MODIS Aqua ocean color sensor (hereafter: MODIS) has been a primary data stream for chlorophyll, serving as an input for operational tools like WhaleWatch, which aims to reduce ship strike risk to blue whales (Hazen et al., 2017), the Sargassum Watch System, which detects and tracks pelagic Sargassum floats (Dierssen et al., 2015), and the California Harmful Algae Risk Mapping system (Anderson et al., 2016). However, MODIS has now surpassed its designed lifespan, and operational tools that rely on MODIS will need to switch to its designated replacement (VIIRS) or to a blended product to maintain continuous observations. While differences between chlorophyll estimates are well documented (Mélin, 2009; Belo Couto et al., 2016; Barnes et al., 2019; Hu et al., 2019), the propagation of those differences into operational downstream products is relatively unexplored (but see Hu et al., 2015, Skakun et al., 2018, Ford et al., 2012).

Here we use an existing operational tool, EcoCast, as a case-study to quantify downstream impacts of transferring between chlorophyll products. EcoCast is a dynamic ocean management tool for fisheries sustainability developed for a swordfish fishery that operates off the U.S. west coast within the California Current Ecosystem (Hazen et al., 2018; Welch et al., 2018). EcoCast currently uses MODIS chlorophyll among other environmental variables to predict habitat suitability for target and bycatch species, and will need to transfer to a different environmental data stream. Here we explore the impacts of transferring EcoCast to VIIRS, the intended replacement for MODIS, to understand the mechanisms of difference propagation through downstream products. Known differences between MODIS and VIIRS are present in waters off the U.S. west coast (Kahru et al., 2014, 2015), and quantifying how these differences propagate into EcoCast downstream products can help elucidate potential impacts in other operational tools. Additionally, we test if downstream differences can be minimized by transferring EcoCast to blended chlorophyll products, which merge estimates across sensors and may therefore result in reduced downstream discrepancies compared to the novel VIIRS sensor.

Evaluating the differences between chlorophyll products can be challenging and time-consuming. To illustrate this problem beyond the California Current Ecosystem, we present a global overview of the spatial and temporal differences between chlorophyll estimates from MODIS, VIIRS, and three blended products. We also present an interactive web application that allows end-users to explore product differences in their time period and region of interest. This work highlights the complexity of transferring operational tools between different environmental data streams, and the need to evaluate downstream impacts before implementation.

2. Methods

2.1. Chlorophyll product background

2.1.1. Single sensor chlorophyll products

The MODIS sensor onboard the Aqua satellite was launched by NASA in 2002. Designed with a five-year lifespan (Lindsey and Herring, 2000), MODIS is now well beyond its intended period of operations. NASA has reported calibration issues for the sensor that have impacted the quality of the time-series since 2009, with significant impacts documented since 2012 (ACRI-ST GlobColour Team, 2017; OBPG, 2015). Ocean color measurements became part of the suite of operational observations made by NOAA under the Joint Polar Satellite System (JPSS) program, and the continuity of U.S. ocean color sensors was insured in 2011 when JPSS launched the first VIIRS sensor on the SNPP satellite. A second VIIRS sensor was launched on the JPSS-1 satellite (since renamed NOAA-20) in 2017, with additional VIIRS sensors planned for launch at five-year intervals until 2036. VIIRS sensors have the advantage over the MODIS sensor of having a wider swath width, although calibration issues have been noted (Garnesson et al., 2019). NASA and NOAA both process VIIRS data, but use different methodologies (Barnes et al., 2019). This present study uses MODIS data produced by NASA's Ocean Biology Processing Group (the 2018 reprocessing) using the standard OC3 band ratio algorithm merged with the color index (CI) of Hu et al. (2012), and VIIRS data produced by NOAA/STAR Ocean Color Team through NOAA Multi-Sensor Level 1 to Level 2 processing system (MSL12) using an improved calibration for the satellite data record (OC-SDR) (Wang et al., 2017). Both chlorophyll products are distributed by NOAA/SWFSC/Environmental Research Division and the West Coast Node of NOAA CoastWatch, available from the ERDDAP data server (Simons, 2019).

2.1.2. Blended chlorophyll products

The GlobColour project was funded in 2005 by the European Space Agency to produce a consistently calibrated time-series of chlorophyll with the highest possible spatial coverage (ACRI-ST, 2007). To maximize time-series longevity, GlobColour creates blended products from four sensors: SeaWiFS, MERIS, MODIS-Aqua, and VIIRS, producing a 20+ year time-series from 1997 to present. Two different products are served by GlobColour: one is a weighted average of Level 2 sensor chlorophyll estimates adjusted to MERIS using the OC4Me algorithm (AVW) and the other blends Level 3 normalized water-leaving radiances across sensors using the GSM model (Maritorena and Siegel, 2005) before producing chlorophyll estimates (GSM). Blended GlobColour products are served by both Hermes (http://hermes.acri.fr) and Copernicus Marine Environment Monitoring Service (http://marine.copernicus.eu).

The European Space Agency's Ocean Color Climate Change Initiative (OC-CCI) was formed to produce a consistent, stable, and error characterized chlorophyll product that meets the standards required for Essential Climate Variables (Belo Couto et al., 2016). Chlorophyll is one of 54 Essential Climate Variables, which are physical, biological, or chemical variables that critically contribute to the characterization of the Earth's climate (Bojinski et al., 2014). The Essential Climate Variables are subject to rigorous monitoring principles, and are required to support the work of the Intergovernmental Panel on Climate Change. The OC-CCI chlorophyll product is produced by shifting the wavelengths of MERIS, MODIS, and VIIRS to match the wavelengths of SeaWiFS (412, 443, 490, 510, 555 and 670 nm), and then applying a bias correction before merging and producing downstream chlorophyll estimates using the OC4v6 algorithm (Jackson and Grant, 2016; O'Reilly et al., 2000). The OC-CCI chlorophyll time-series is updated several times per year; at the time of analysis the timeseries spanned from 1997 to six months before the present. The present study uses the version 3.1 chlorophyll product (Sarthyendranath et al., 2018) which is served by OC-CCI (https://www.oceancolour.org) and the

ERDDAP data server (Simons, 2019) co-operated by NOAA/SWFSC/ Environmental Research Division and the West Coast Node of NOAA CoastWatch.

2.2. EcoCast case-study

The fisheries sustainability tool EcoCast (Hazen et al., 2018) was used as a case-study to explore the mechanisms by which differences between chlorophyll products propagate into the downstream products of operational tools. EcoCast was developed by a collaboration of academic, governmental, and non-governmental organizations to address bycatch issues in California's Drift Gillnet Fishery. Launched for on-the-water use in 2018 (Welch et al., 2018), EcoCast is designed to help fishers identify waters off the U.S. west coast that are better or poorer to fish each day based on the relative habitat suitability for the target species, swordfish *(Xiphias gladius),* and bycatch species: leatherback turtles *(Dermochelys coriacea)*, California sea lions *(Zalophus californianus)*, and blue sharks *(Prionace glauca)*. Each day, EcoCast acquires the most recent remote sensing data for chlorophyll and other variables to predict habitat suitability for target and bycatch species in real-time. To predict habitat suitability, EcoCast applies boosted regression tree models to the newly acquired environmental data for each day (see description of models in Hazen et al., 2018). One model exists for each species with the exception of blue sharks, for which two models were built in order to utilize data from fisheries observers and satellite tags (blue shark-O and blue shark-T, respectively). Because boosted regression trees have natural stochasticity in model fitting, 10 iterations of each model were averaged to produce daily habitat suitability predictions for each species. The species habitat suitability predictions for each day were assimilated using a weighted algebraic algorithm to produce integrated surfaces of fishing suitability (Hazen et al., 2018).

The boosted regression tree models were fit using species datasets spanning 1990–2014, and as such models were fit using chlorophyll data from both SeaWiFS and MODIS (Hazen et al., 2018). Species records from 1997 to 2003 were associated with SeaWiFS chlorophyll, records from 2003 to 2014 were associated MODIS chlorophyll, and record prior to 1997 was removed due to lack of overlap with a science-quality chlorophyll product. When EcoCast was operationalized in 2018, daily 8-day rolling average chlorophyll products from MODIS were used for model prediction. Due to the longevity of the species records dataset, there is insufficient overlap with the VIIRS chlorophyll time-series (2012-present) to refit the boosted regression tree models. Instead, we test for differences in model predictions based on MODIS and VIIRS chlorophyll to capture impacts of operational model transfer.

Time-series of 8-day rolling averages for MODIS and VIIRS chlorophyll (Appendix S1; Table S1) were downloaded for each day in the 2015–2018 fishing seasons (August–December, inclusive). Daily time-series for Globcolour AVW, Globcolour GSM, OC-CCI blended products (Appendix S1; Table S1) were downloaded for each day in the 2015–2018 fishing seasons and converted into 8-day rolling averages to match the temporal resolution of the MODIS and VIIRS products. The five species boosted regression tree models were predicted using each of the five 8-day rolling average chlorophyll time-series to produce time-series of species habitat suitability (n = 5 for each species; n = 25 in total). Then, the weighted algebraic algorithm was run to integrate the species habitat suitability predictions to produce time-series of fishing suitability based on each of the chlorophyll time-series (n = 5).

To explore the mechanisms by which differences between MODIS and its intended replacement – VIIRS – propagates into EcoCast downstream products, the time-series of MODIS and VIIRS-based products (log MODIS and VIIRS chlorophyll, MODIS- and VIIRS-based species habitat suitability, MODIS- and VIIRS-based fishing suitability) were restricted to days and pixels with data for both MODIS and VIIRS to remove the effect of differences in temporal and spatial coverage. To test if differences can be minimized by transferring EcoCast to a blended product as opposed to VIIRS, the time-series for MODIS, VIIRS, Globcolour AVW, Globclour GSM, and OC-CCI-based products were restricted to days and pixels with data for all five chlorophyll products. These two analyses were handled separately to preserve as much data as possible in the two product MODIS/VIIRS comparison (379 days with data common to both products compared to 277 days with data common to all five products). The time-series for each product was then standardized between zero and one to allow direct comparison, subtracted from its MODIS-based time-series counterpart to calculate inter-product difference, and tested for significance using ANOVA in the R “stats” package (R Core team, 2019).

2.3. Global analysis

Monthly composites of global single sensor products (MODIS, VIIRS) and blended products (GlobColour AVW, GlobColour GSM, OC-CCI) were downloaded between 2012 and 2018 (Appendix S1; Table S1). Only months with data for all five products (n = 77) were considered for further analysis. For each month, the pixels retrieved for each global product were restricted to areal extents with data common to all products in order to remove the effect of differences in spatial coverage. To capture temporal difference between products, spatial means of log chlorophyll were calculated for each month and product. To capture spatial differences between products, log chlorophyll was averaged across all months for each product and each grid cell. Areas of anomalously high and low spatial differences between products were assessed by identifying pixels greater or < 1.5 standard deviation of the mean of all products.

3. Results

3.1. EcoCast case-study

Chlorophyll estimates in the California Current Ecosystem were significantly higher in MODIS than in VIIRS across the time-series (Fig. 1A, Table 1; $p < 0.0001$). This significant difference propagated into species habitat suitability predictions and EcoCast fishing suitability, with higher values predicted from MODIS for all cases except blue shark-T and sea lions (Fig. 1B, Table 1; $p < 0.0001$). The largest absolute mean difference between MODIS- and VIIRS-based time-series was found in the swordfish predictions (difference = 0.031, Table 1), followed by EcoCast fishing suitability, chlorophyll estimates, blue shark-O, blue shark-T, sea lions, and lastly leatherbacks with the smallest difference (difference = 0.006, Table 1). Differences were highly variable across the species habitat suitability predictions; however, this variability was not related to chlorophyll importance in the models (Table 1, Appendix S2; Fig. S1). Differences between MODIS and VIIRS for all products were significant ($p < 0.0001$; Table 1).

Differences between MODIS and VIIRS chlorophyll estimates were dependent on chlorophyll concentration (Fig. 2A) with MODIS producing higher estimates at low concentrations (< -0.51 log mg m^{-3}), and VIIRS producing higher estimates at high concentrations (> -0.51 log mg m^{-3}). Spatially, these differences created a cross-shore gradient with higher VIIRS estimates in nearshore productive waters (Fig. 2B) and higher MODIS estimates in offshore oligotrophic waters (Fig. 2C). This spatial gradient persisted in downstream predictions of species habitat suitability and the EcoCast fishing suitability (Fig. 2D–F).

Across time, MODIS-VIIRS differences were highly variable within and between chlorophyll estimates and downstream products. MODIS chlorophyll estimates were generally higher in all days, except at the end of 2018, when VIIRS estimates became higher (Fig. 3A). The variability of difference in downstream species habitat suitability predictions (Fig. 3B) was related to the shapes of the chlorophyll response curves in the boosted regression tree models (Fig. 4, Appendix S2; Fig. S2). For example, predicted swordfish habitat suitability was much higher based on MODIS than on VIIRS during the fall of 2017 (Fig. 3B,

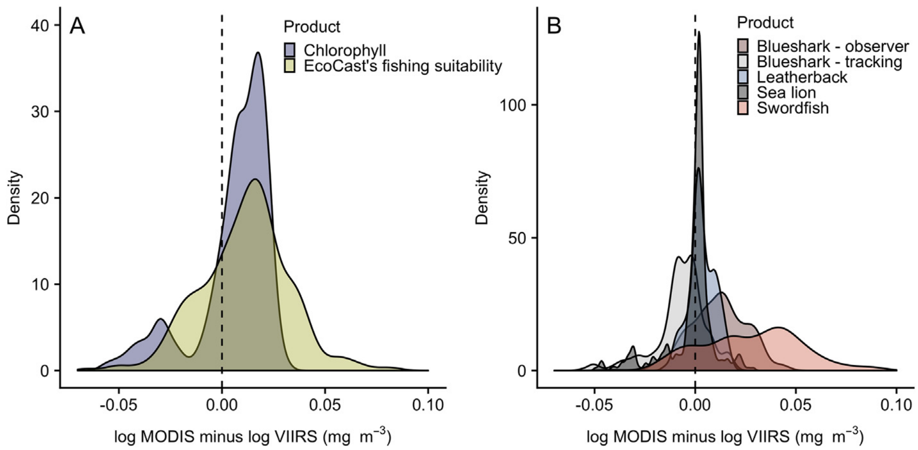

Fig. 1. The distribution of difference between MODIS and VIIRS across the time-series for A) chlorophyll estimates and EcoCast integrated fishing suitability, B) habitat suitability for the five species. Positive and negative values on the x-axis indicate MODIS-based products are higher and lower than VIIRS-based products, respectively.

Box 1), which was caused by the distribution of MODIS chlorophyll values during this time being shifted to the right relative to the VIIRS distribution, and overlapping more with high values in the response curve (Fig. 4A). Similarly, predicted sea lion habitat suitability during winter 2018 was higher based on VIIRS (Fig. 3B, Box 2), when the chlorophyll distribution during this time overlapped with high values of the response curve peak (Fig. 4B). In contrast, leatherback habitat suitability predictions were very similar between the two chlorophyll products across the time-series (Fig. 3B); as both the MODIS and VIIRS distributions overlapped similarly with a trough in the response curve (Fig. 4C).

Downstream differences in EcoCast fishing suitability were not reduced by using a blended product as opposed to VIIRS (Table 2). Differences in chlorophyll estimates and EcoCast fishing suitability were smallest when transferring to VIIRS (mean difference from MODIS 0.0207 and 0.0039, respectively) and largest when transferring to Globcolour GSM (mean difference from MODIS 0.049 and 0.0121, respectively) (Table 2). Chlorophyll estimates and EcoCast fishing suitability were significantly higher in MODIS than in VIIRS, Globcolour AVW, Globcolour GSM, or OC-CCI across the time-series (Table 2; $p < 0.0001$). Spatially, the chlorophyll estimates from the three blended products differed most from MODIS estimates inshore, where blended estimates were significantly lower than MODIS (Fig. 5B–D). Cross-shore gradients were also apparent in comparisons of MODIS-based fishing suitability and fishing suitability based on the other four products. MODIS-based fishing suitability was higher offshore and fishing suitability based on VIIRS, Globcolour AVW, Globcolour GSM, and OC-CCI was higher inshore (Fig. 5E–H).

3.2. Global analysis

We compared the five chlorophyll products globally to help identify areas beyond the California Current Ecosystem where tools transfer is likely to be more or less problematic. Globally, the five chlorophyll products were most similar in open ocean waters at mid to low latitudes, with disagreement between products more apparent towards the poles (Fig. 6). GlobColour GSM and MODIS had the most anomalously high estimates (*i.e.* pixels with concentrations greater than the mean of all products plus 1.5 standard deviations). VIIRS and OC-CCI had anomalously low pixels with respect to the mean of all products near both poles, while anomalously low pixels with respect to the mean of all products in the GlobColour AVW imagery were concentrated in the tropical Atlantic. In general, chlorophyll concentrations in subtropical ocean gyres were consistent across products, while concentrations in major ocean currents had the most disagreement between products (Fig. 6). For example, pixels in the North Pacific Current were anomalously high with respect to the mean of all products in GlobColour GSM and MODIS, and anomalously low with respect to the mean of all products in VIIRS and OC-CCI (Fig. 6, Appendix S3; Fig. S1). Gulf Stream pixels were also anomalously high with respect to the mean of all products in GlobColour GSM and MODIS, and anomalously low with respect to the mean of all products in VIIRS and OC-CCI (Fig. 1, Appendix S1; Fig. S2). Monthly time-series of chlorophyll products showed similar relationships between the five products across time, although there were some regional differences (Appendix S3; Fig. S4). To facilitate comparisons between products, we developed the Ocean Color Explorer (https://heatherwelch.shinyapps.io/oceancolorexplorer/), an interactive R shiny web application that allows end-users to compare time-series of the five chlorophyll products for their area and time period of interest.

4. Discussion

Operational tools often rely on satellite remote sensing instruments that have finite life spans. Our study highlights the complexities of transferring operational tools across environmental data streams, and

Table 1
Mean difference and mean absolute difference between MODIS- and VIIRS-based chlorophyll and downstream products of habitat suitability for the five species and EcoCast fishing suitability, with F and *p* values from an ANOVA. For each product, difference is calculated by subtracting the VIIRS time-series from the MODIS time-series. Mean difference indicates if values are on average higher in MODIS or VIIRS (positive and negative values, respectively); mean absolute difference indicates the average magnitude of difference regardless of directionality. For the five species, the importance (%) of chlorophyll in boosted regression tree models are also reported.

Product	Chlorophyll importance	Mean difference	Mean absolute difference	$F_{(1,\ 1,798,632)}$	p value
Chlorophyll		0.006	0.016	2287.30	< 0.0001
Blueshark - observer	2.42	0.012	0.015	1737.29	< 0.0001
Blueshark - tracking	9.97	−0.007	0.010	642.59	< 0.0001
Leatherback	12.23	−0.002	0.007	32.89	< 0.0001
Sea lion	11.09	0.003	0.006	140.37	< 0.0001
Swordfish	6.74	0.028	0.031	10,870.85	< 0.0001
EcoCast fishing suitability		0.011	0.020	2601.19	< 0.0001

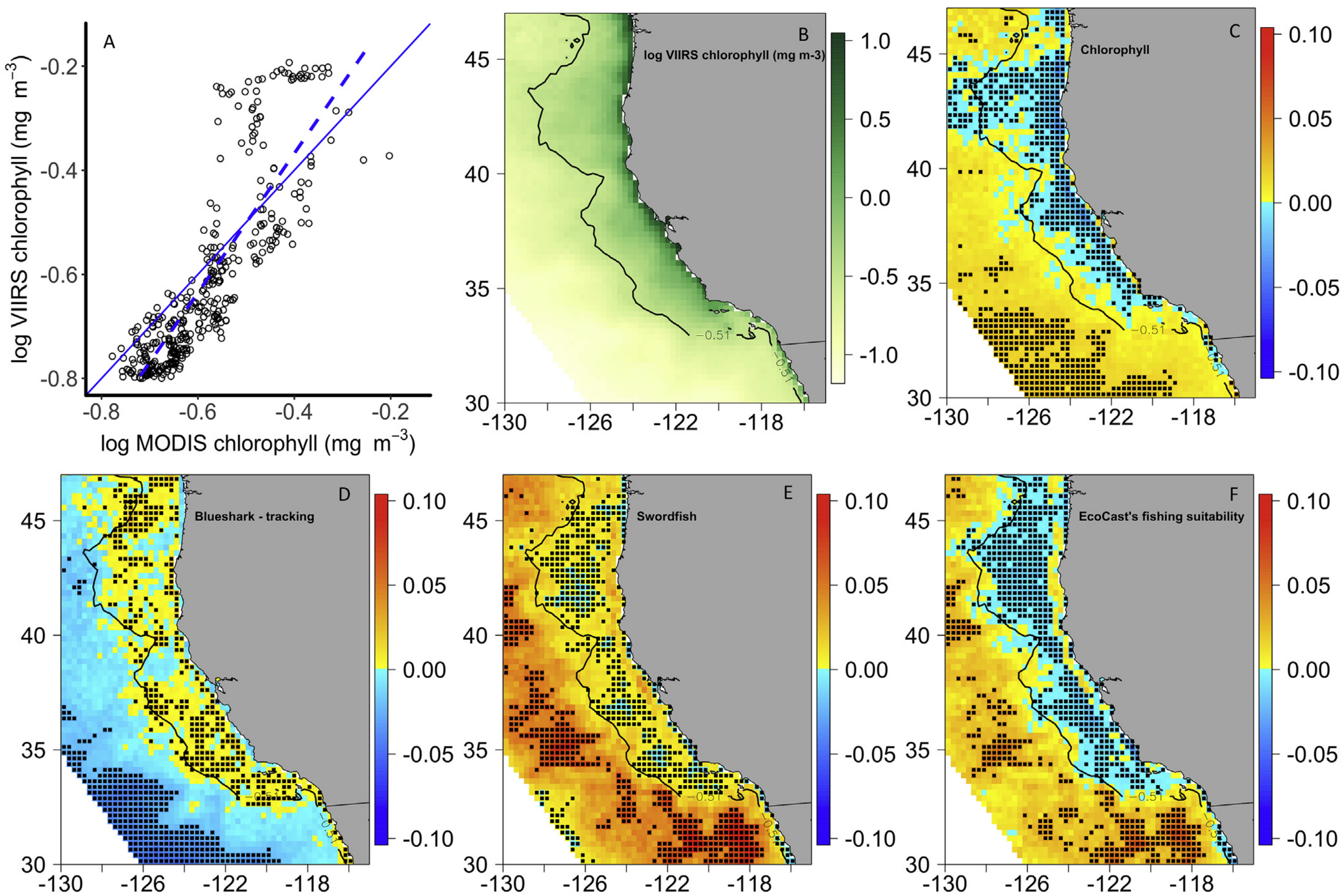

Fig. 2. Spatial differences between MODIS and VIIRS chlorophyll *a*nd downstream products: A) Daily mean MODIS and VIIRS chlorophyll estimates in the case-study region with a linear fit between them (dashed line) and the one-to-one line (solid line). B) Mean VIIRS chlorophyll for 2012–2018. The black contour at log (chlorophyll) = -0.51 mg m^{-3} separates productive inshore waters from oligotrophic offshore waters. Differences between MODIS and VIIRS for C) chlorophyll, D) blue shark-T habitat suitability, E) swordfish habitat suitability, and F) EcoCast fishing suitability. C–F) Plots show MODIS minus VIIRS for each product. Hatching indicates where differences are larger than one standard deviation from the spatial mean of difference.

revealed the downstream impacts caused by this transfer. Using an operationalized tool for fisheries sustainability as a case-study, we found that differences between two chlorophyll products (MODIS and VIIRS) did not linearly propagate through tool downstream products, and were affected by the statistical procedures applied during tool workflow. We show significant spatial and temporal differences between chlorophyll products at a global scale, demonstrating that this problem is not unique to the U.S. west coast. Below we explore the mechanisms of downstream difference propagation in the case-study tool, and the factors that contribute to global and regional discrepancies between chlorophyll products. These considerations can help guide decision-making regarding the transfer of operationalized tools between different chlorophyll products.

Transitioning from MODIS to VIIRS produced unexpected impacts in model predictions of species habitat suitability and EcoCast integrated surface of fishing suitability. Differences in species habitat suitability were dictated by the change in overlap between MODIS and VIIRS chlorophyll distributions and the model-specific chlorophyll response

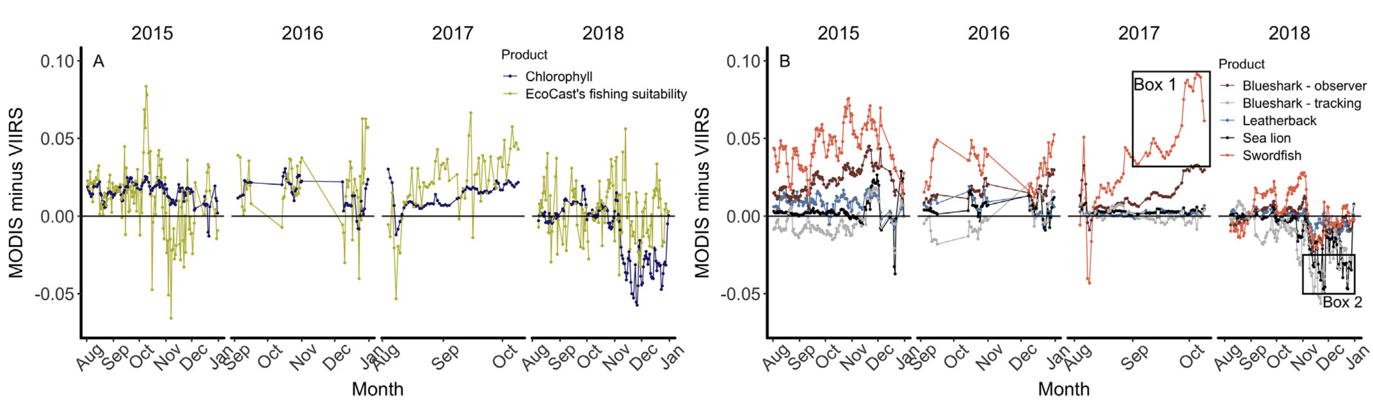

Fig. 3. Time-series of spatially-averaged differences between MODIS and VIIRS in the case-study region for A) chlorophyll *a*nd EcoCast fishing suitability, and B) habitat suitability for the five species. Plots show MODIS minus VIIRS for each product.

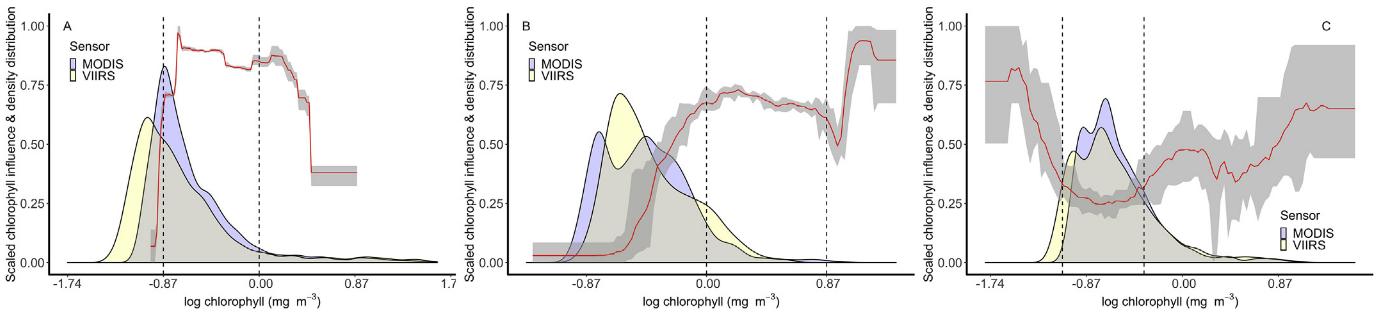

Fig. 4. Relationships between MODIS/VIIRS chlorophyll distributions and species response curves for three different species and time periods: A) swordfish in fall 2017, B) sea lions in winter 2018, and C) leatherback turtles for the full study period (2015–2018). Response curve means are shown in red and ranges across the ten iterations of each model are shown in grey fill.

Table 2
Mean difference and mean absolute difference between MODIS-based products (chlorophyll and EcoCast fishing suitability) and products based on VIIRS, GlobColour AVW, GlobColour GSM, and OC-CCI, with F and p values from an ANOVA. For each product, difference is calculated by subtracting the non-MODIS time-series from the MODIS time-series.

	Product	Mean difference	Mean absolute difference	$F_{(1,\ 162,366)}$	p value
Chlorophyll	AVW	0.0273	0.0273	784.97	< 0.0001
	GSM	0.049	0.0498	4061.25	< 0.0001
	OC-CCI	0.0351	0.0353	1315.44	< 0.0001
	VIIRS	0.0207	0.0211	521.59	< 0.0001
EcoCast fishing suitability	AVW	0.0063	0.0081	46.71	< 0.0001
	GSM	0.0121	0.015	178.18	< 0.0001
	OC-CCI	0.0063	0.0083	43.52	< 0.0001
	VIIRS	0.0039	0.0108	21.3	< 0.0001

curves. This impact was variable between and within species across time. Interestingly, we found the greatest difference between MODIS- and VIIRS-based time-series in the swordfish habitat suitability predictions, which was larger than that for the chlorophyll estimates and for EcoCast fishing suitability. For all other species, habitat suitability differences were lower than differences in the chlorophyll estimates, likely due to the low importance of chlorophyll relative to other covariates in the species models (Appendix S2; Fig. S1). Differences in EcoCast fishing suitability were reduced by a canceling out effect of species-specific habitat suitability differences (Tables 1, 2). This suggests that integrated tool products can exhibit reduced or enhanced differences depending on whether individual species differences are in opposition or in agreement.

These results are likely affected by the species model type, species biology, and study region of the case-study analysis. For example, species model types that allow for non-linear responses to chlorophyll, compared to linear responses, may be more sensitive to differences between chlorophyll products. Additionally, non-linear responses in the boosted regression tree models used here typically have sharper step-wise transitions between response values because the models use binary splits to relate species responses to predictors. These sharper transitions likely have larger impacts on downstream products relative to non-linear models that produce smoother responses curves, *e.g.* generalized additive models.

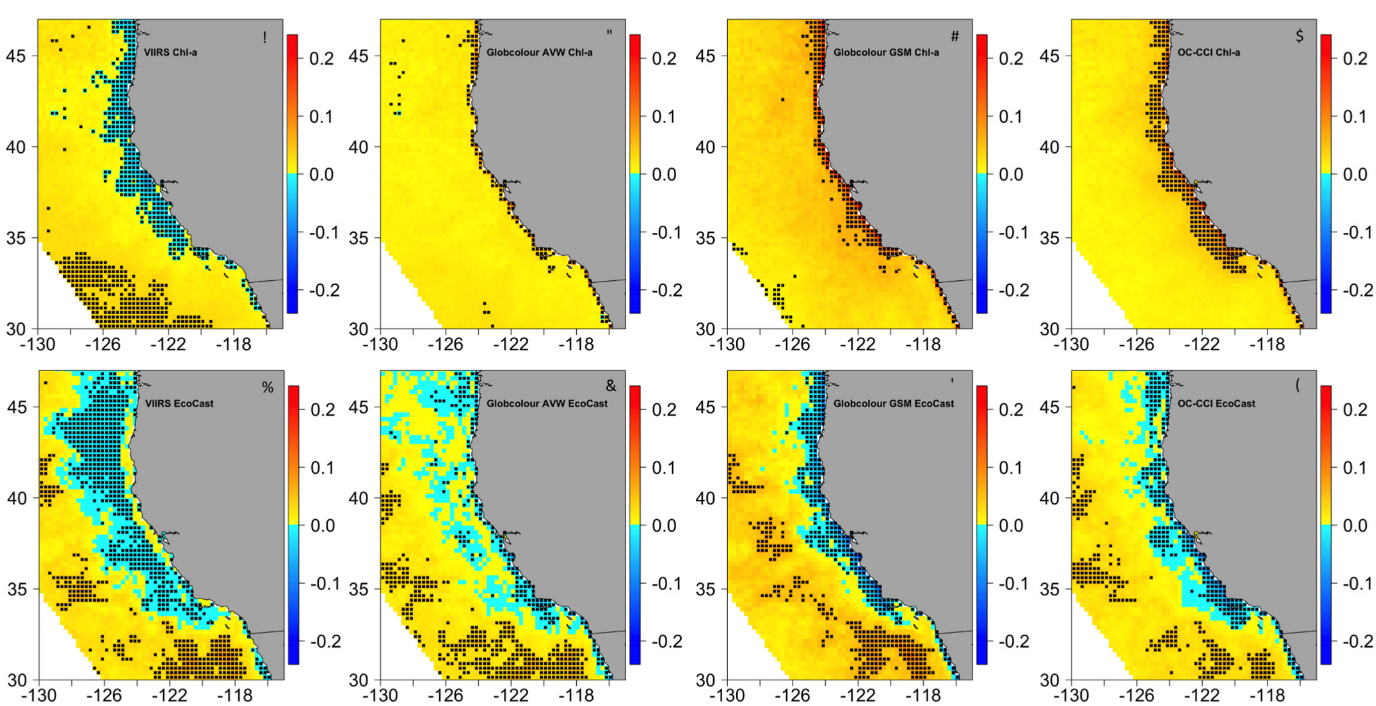

Fig. 5. Spatial difference between MODIS and VIIRS-, GlobColour AVW-, GlobColour GSM-, and OC-CCI-based chlorophyll *and* EcoCast fishing suitability. For each product, differences are calculated by subtracting the non-MODIS time-series from the MODIS time-series. Hatching indicates where differences are larger than one standard deviation from the spatial mean.

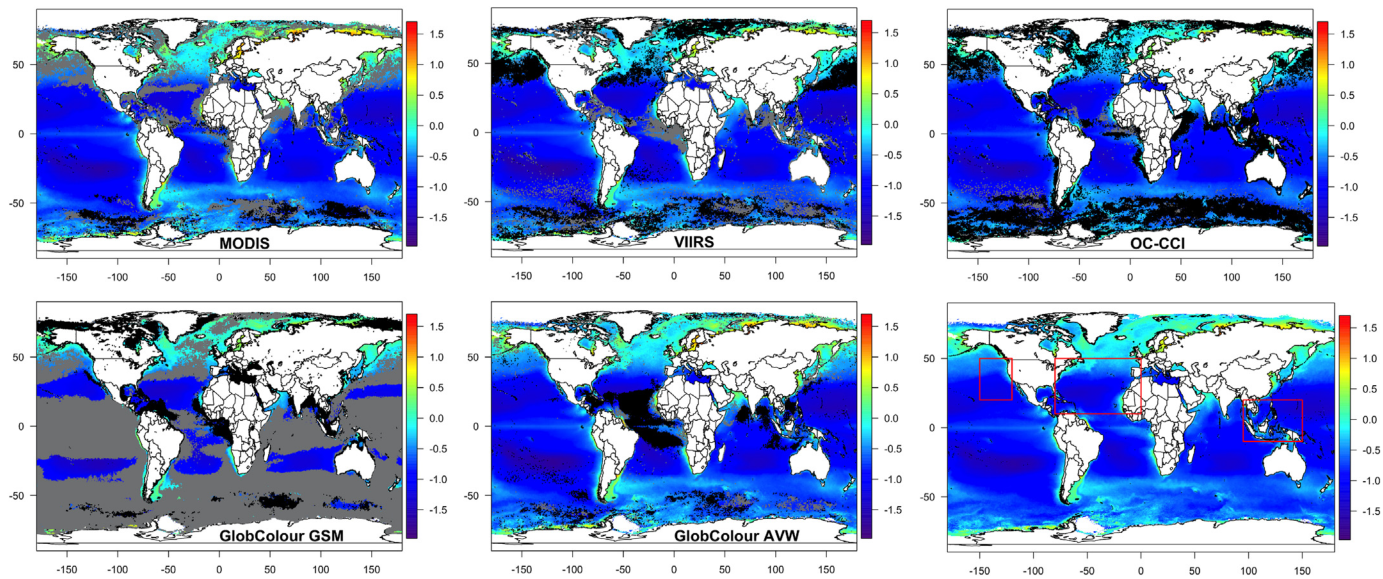

Fig. 6. Long-term average of five global chlorophyll products from 2012 to 01 to 2018–06, the time-series common to all products. Scale bar shows log chlorophyll concentration (mg m^{-3}). Grey and black color pixels are areas that have concentrations greater and < 1.5 standard deviation from the mean of all products, respectively. Bottom right plot shows the bounding boxes of regional analyses in Appendix S3, superimposed over the mean of all products.

Species biology can also play a role in how chlorophyll differences affect downstream products. In the present study, chlorophyll had relatively minor importance in the species models relative to the other environmental covariates (~2–12% explanatory power; Table 1). The relative importance of chlorophyll in a species model may impact the magnitude of difference between model predictions based on different chlorophyll products. Finally, results might be affected by study region, as relationships between chlorophyll products has been shown to vary regionally (Djavidnia et al. 2010). Additionally, the relationship between VIIRS and MODIS chlorophyll estimates can vary when compared over larger ranges of concentration (Kahru et al., 2015). Thus, specific results presented here are not necessarily transferrable to other models, species, and regions. However, these considerations contribute to our general understanding of the mechanisms by which differences between chlorophyll products propagate through the workflow of operational tools.

Differences in EcoCast fishing suitability were not reduced by transitioning from MODIS to a blended chlorophyll product (GlobColour GSM, GlobColour AVW, or OC-CCI) as opposed to VIIRS (Table 2), highlighting the challenge of transferring operational tools between products. This result is perhaps to be expected considering the efforts that have gone into maintaining the continuity between the MODIS and VIIRS chlorophyll products (Wang et al., 2016). The blended products, in contrast, were developed to provide continuous chlorophyll datasets merged over multiple satellite missions. These results suggest that ultimately, tool developers should aim to eliminate the need to transition between chlorophyll products by taking advantage of the long time-series of the blended products during initial operationalization. However, blended products might still show artefacts due to unaccounted differences between missions, and it will be important to test how tool outputs vary across time as new missions are added into blended products. For tools that are already operationalized on a single-sensor product and cannot avoid the transfer problem, tool developers should compare the available chlorophyll products to determine which have the most alignment with the currently utilized product over the spatial domain of the tool.

Comparison of VIIRS and blended chlorophyll products to MODIS revealed high disagreement for both chlorophyll *and* fishing suitability in productive inshore waters (Fig. 5). Chlorophyll estimation in these productive waters is more difficult than in generally oligotrophic Case 1 waters (Morel et al., 2007). Regionally optimized chlorophyll algorithms are frequently applied in coastal waters to correct remote sensing estimates to better fit *in-situ* data (*e.g.* Jiang et al., 2017; Yoon et al., 2019). A regionally-tuned algorithm that additionally aims to minimize inter-sensor differences exists for the California Current Ecosystem (Kahru et al., 2012), and could potentially alleviate challenges associated with inshore chlorophyll estimation and operational tool transfer. However, these corrected chlorophyll estimates are not produced in near-real-time, which is a requirement for operational tools such as EcoCast. Producing and serving these regionally corrected estimates in near-real-time could facilitate the development of operational tools in the California Current Ecosystem.

Global comparison of the five chlorophyll products revealed that challenges associated with tool transfer are likely to persist beyond the EcoCast domain. As with the California Current Ecosystem, global inshore waters generally displayed the highest disagreements among products. In these Case 2 waters, variations in water optical quality are driven by suspended inorganic materials and other substances in addition to phytoplankton, making chlorophyll estimations in more complex. Additionally, waters in optically-complex and productive regions like transition zones, fronts, upwelling regions, and high latitudes showed higher disagreement between products. Case 1 open ocean waters had high inter-product similarity, consistent with previous results (Djavidnia et al., 2010). In Case 1 waters, phytoplankton are primarily responsible for the optical signal, making chlorophyll estimates in these waters relatively straightforward (Bailey and Werdell, 2006; IOCCG, 2000). These results suggest that inter-product comparisons prior to transfer will be especially important for tools that operate in inshore waters and in productive, optically-complex open ocean waters.

4.1. Future directions

Additional factors to consider regarding tool transfer include data currency requirements, and the purpose of the tool. While most products are available in near real-time, the OC-CCI product is updated several times during the year and currently has a six-month lag, making it unsuitable for tools that require near real-time data. The intended purpose of the tool will also affect product choice. Tools that aim to capture long-term trends should consider the OC-CCI product, which targets climate quality consistency with minimal inter-sensor bias (Belo Couto et al., 2016; Mélin et al., 2017). Tools that aim to monitor short-term fluctuations might perform better with a single sensor product or one of the GlobColour products, which are available as near-real time products and reprocessed historical time-series (Belo Couto et al., 2016; Mélin et al., 2017).

Lastly, differences in data density caused by cloud cover, aerosols, and sun glint will affect product choice. Data density (*i.e.* the frequency of missing data in pixels across time) will vary between products, for example MODIS has higher data density than VIIRS and the three blended products in waters offshore the U.S. west coast (Appendix S2; Fig. S3). Gap-filling procedures such as spatial interpolations and Data INterpolating Empirical Orthogonal Functions (DINEOF), which interpolates across both space and time, can help alleviate issues surrounding data density (Beckers and Rixen, 2003). Data assimilative ocean models, which combine available observations with a regional circulation model to produce ocean state estimates, offer another gap-free alternative. Physical outputs from these models have been used to inform fisheries tools off the U.S. west coast (Abrahms et al., 2019; Welch et al., 2019b), and similar products for chlorophyll are in development (Mattern et al., 2017). Additionally, for tools that utilize species distribution models, gap filling may be done at the modeling stage by model types that implicitly deal with missing data, such as the boosted regression trees utilized in the EcoCast case-study.

The wide variety of reprocessing versions, ocean color algorithms, and available chlorophyll products mean that caution should be employed when extrapolating our results beyond the specific products and time-series explored here. Results might differ if different products were used, such as the NASA VIIRS chlorophyll product or version 4 of the OC-CCI product released June 2019. For example, a global comparison of products between 2002 and 2007 found GlobColour GSM estimates to be higher than OC-CCI estimates, consistent with our results, while GlobColour AVW estimates and MODIS estimates were higher and lower than OC-CCI estimates, respectively (Belo Couto et al., 2016), opposing the results of this study. Another global analysis conducted from 1997 to 2019 found MODIS estimates to be higher than VIIRS estimates (Garnesson et al., 2019), as did a regional analysis from 2012 to 2013 in waters around Southeast Asia (Nuris et al., 2017), with both studies consistent with our results. End-users should take care to compare the specific version of the products they intend to use in their region and time period of interest. Additionally, this work aimed to understand inter-product differences, and did not examine product accuracy as compared to *in situ* data. GlobColour GSM was found to have the lower error compared to *in situ* data than GlobColour AVW and MODIS (Ford et al., 2012). However, chlorophyll products show regional accuracy biases to observed data (Bailey and Werdell, 2006) and if available, it would be useful to compare products to *in situ* water samples to aid in product selection (see an example in Kahru et al., 2014).

While it is one thing to highlight the importance of cross-product comparisons, in practice we understand that these comparisons can be costly in terms of time and computing resources, and are frequently only a small component of the overall project objectives. To decrease the workload associated with product selection, we developed the open access Ocean Color Explorer. Additionally, online tools like the SWFSC/Environmental Research Division's ERDDAP (https://coastwatch.pfeg.noaa.gov/erddap/) graphic explorer (Simons, 2019) and NASA Giovanni's time-series plotter (https://giovanni.gsfc.nasa.gov/giovanni/) can aid in product comparison. Lastly, expert opinion is an invaluable source of product expertise and each product has a readily accessible contact team available to field questions and aid interpretation, for example the NASA OceanColor forum (https://oceancolor.gsfc.nasa.gov/forum/oceancolor/forum_show.pl). These resources can aid operational tool product transfer, ensuring continuous characterization and monitoring of our ecosystems.

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CRediT authorship contribution statement

H. Welch:Conceptualization, Methodology, Formal analysis, Writing - original draft.**S. Brodie**:Validation, Writing - review & editing.**M.G. Jacox**:Validation, Resources, Writing - review & editing, Funding acquisition.**D. Robinson**:Methodology, Resources, Writing - review & editing.**C. Wilson**:Methodology, Validation, Writing - review & editing, Funding acquisition.**S.J. Bograd**:Methodology, Writing - review & editing, Funding acquisition.**M.J. Oliver**:Writing - review & editing, Funding acquisition.**E.L. Hazen**:Conceptualization, Methodology, Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Corrigendum

Corrigendum to “Considerations for transferring an operational dynamic ocean management tool between ocean color products”. Remote Sensing of Environment 242 (2020) 111753

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The authors regret misspelling the lead author's last name while citing Sathyendranath et al. (2018). Additionally, the authors would like to offer a corrected description of the OC-CCI product. The OC-CCI chlorophyll product is produced by shifting the wavelengths of MERIS, MODIS, and VIIRS to match the wavelengths of SeaWiFS (412, 443, 490, 510, 555 and 670 nm), and then applying a bias correction before merging and producing downstream chlorophyll estimates using a blended combination of the OCI, OC5, and OC3 algorithms (Jackson and Grant, 2016; O'Reilly et al., 2000).

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