Dependence of satellite ocean color data products on viewing angles: A comparison between SeaWiFS, MODIS, and VIIRS

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Despite widespread use of satellite ocean color data, measured radiance and derived geophysical parameters (e.g., remote sensing reflectance or $R_{rs}$, chlorophyll a concentration, absorption and scattering coefficients, diffuse attenuation coefficients) may show inconsistencies according to the sensor viewing geometry. In particular, data fluctuations based on sensor zenith angle (SZA) can cause variable uncertainties in derived time series, as well as regional or global means. This study analyses single- and merged-sensor datasets from SeaWiFS, MODIS, and VIIRS for the Gulf of Mexico region, finding pronounced variation within and between satellites as a function of SZA. Such effects are generally restricted to data with SZA above 40°, although large variation exists between satellites and products. The non-tilted MODIS and VIIRS also show residual errors during summer time for SZA < 30° due to imperfect sun glint and bidirectional reflectance distribution function (BRDF) corrections. Furthermore, certain algorithms and products are more resilient to angular dependence in $R_{rs}$. Overall, this study provides a framework for interpretation and account of SZA dependence in satellite ocean color data products, towards creation of cross-sensor time series as required for analysis of changes on multi-decadal scales. Finally, these findings can inform design and calibration of future geostationary sensors, for which targets have fixed viewing geometry.

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1. Introduction

Earth observing satellite platforms offer a means by which local and global ocean changes may be assessed. The synoptic spatial coverage and high repeat sampling frequency afforded by these systems surpasses that possible with in situ measurement. As such, among other agencies (e.g., the European Space Agency), the United States National Aeronautics and Space Administration (NASA) has deployed several ocean color sensors, including the Sea-viewing Wide Field of View Sensor (SeaWiFS, 1997–2010) onboard the OrbView-2 satellite and the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument onboard the satellite Aqua (MODISA, 2002–present), while the National Oceanic and Atmospheric Administration (NOAA) has recently deployed the Visible Infrared Imaging Radiometer Suite (VIIRS, 2011–present) on the Suomi National Polar-Orbiting Partnership (NPP) satellite. These sensors (in particular SeaWiFS and MODIS) have firmly established the field of satellite ocean color, greatly improving understanding of ocean dynamics, global carbon cycling, and ocean productivity, among many others.

Due to time-dependent degradation and eventual failure of these instruments, assessment of decadal changes requires multiple ocean color sensors with accurate (or at least consistent) measurements. Maintaining accuracy for any single sensor requires extensive effort both pre-launch and for the duration of the satellite mission. At NASA, for SeaWiFS/MODIS, and VIIRS ocean color data, this task is undertaken by the NASA Ocean Biology Processing Group (OBPG), with accuracy goals for clear water targets of 5% for blue band remote sensing reflectance ($R_{rs}^0$, sr$^{-1}$) retrievals and 35% for chlorophyll concentration (Chla) derivations (Hooker & Esaias, 1993).

Towards post-launch accuracy maintenance, calibration and validation of $R_{rs}$ measurements from these sensors is completed using several methods, including lunar observations, solar diffuser observations, and ‘matchups’ (collocated and concurrent measurements) between satellite and in situ data (Eplee et al., 2012b). Such efforts have detected (and subsequently resolved) sensor degradation affecting MODIS (Meister, Franz, Kwiatkowska, & McClain, 2012; Meister & Franz, 2014) and VIIRS (Eplee et al., 2012a) data. As a result of these and similar efforts, the percent difference for satellite/in situ $R_{rs}^0$ retrievals is generally less than 20% for SeaWiFS (Bailey & Werdell, 2006; Mélin, Zibordi, & Berthon, 2007; Antoine et al., 2008; Zibordi, Berthon, Mélin, D’Alimonte, & Kaitala, 2009; Maritorena, D’Andon, Mangin, & Siegel, 2010; Cannizzaro et al., 2013), MODIS (Franz, Bailey, Werdell, & McClain, 2007; Mélin et al., 2007; Antoine et al., 2008; Zibordi et al., 2009; Maritorena et al., 2010), and VIIRS (Cao et al., 2013; Hlaing et al., 2013). These results can be improved through account of uncertainties in the in situ measurements (e.g., Hu, Feng, & Lee, 2013), however other sources of uncertainty exist.

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Sensor calibration and validation of products are typically restricted to targets viewed close to nadir, as satellite data product quality degrades at large view angles. Therefore, as a compromise of data quality and data quantity, 60° sensor zenith angle (SZA) has historically been used as a cutoff threshold. Within this SZA range, however, SZA dependence at relatively large angles potentially exist. Differences in satellite design further highlight the necessity of robust angular dependence assessment. Specifically, both SeaWiFS and VIIRS were built with a telescope assembly that rotates to capture the entire swath. For MODIS, however, a mirror rotates to scan the earth, projecting the radiance to a fixed telescope. Unfortunately, mirror reflectivity varies according to angle of incidence, which can cause inconsistencies in derived products (Franz, Bailey, Meister, & Werdell, 2012; Meister & Franz, 2014). Previously, this effect has been corrected using SeaWiFS data (Meister & Franz, 2011) as well as lunar and solar diffuser observations (Xiong, Chiang, Esposito, Guenther, & Barnes, 2003). Meister et al. (2012), however, found this correction to be insufficient for ocean color work, especially for the blue bands. For the most recent MODIS reprocessing, calibration using desert targets in combination with other statistical corrections (in particular, using MODIS center-scan measurements to calibrate data from larger SZAs) shows strong agreement with SeaWiFS data (Meister & Franz, 2014). Angular dependence could also manifest through uncertainties in the bidirectional reflectance distribution function (BRDF; Eplee et al., 2012b). Although this has been addressed through the BRDF correction (Morel & Gentili, 1996), residual errors in Rrs and derived products may remain. Nevertheless, due to the relative scarcity of in situ data of quality high enough to be used for satellite data product validation, robust assessment of SZA dependence using satellite/in situ matchups is difficult. Attempts to quantify SZA dependence using lunar observations and cloud-top radiances have also been inconclusive (Eplee et al., 2012b), although SZA dependence has been noted in MODIS cloud data (Maddux, Ackerman, & Platnick, 2010).

Data from various satellite ocean color sensors, however, may overlap in space and time (Fig. 1) and provide a method by which to assess sensor uncertainties (Franz et al., 2005, 2012; Hu & Le, 2014; Barnes & Hu, 2015). This approach to assessing satellite uncertainties benefits greatly from the huge quantity of matchup data available, which allows for robust statistical assessment and greater confidence in observed trends. Furthermore, satellite/satellite comparisons allow assessment of data as commonly used by researchers, as opposed to a few highly quality controlled points. Overall, very strong agreement (within a few percent) has been observed between MODIS Rrs and matchups measured by SeaWiFS for global oceans (Franz et al., 2005, 2012) or VIIRS for an estuary (Hu & Le, 2014), while derived products show percent difference generally less than 10% (Franz et al., 2012; Barnes & Hu, 2015). Although Barnes and Hu (2015) noted some decline in agreement between satellite water clarity measurements according to increasing SZA, angular dependence of Rrs, and other derived products has not been sufficiently elaborated.

Provided there is overlap between current and future polar orbiting satellite sensors [e.g., the planned Pre-Aerosol, Clouds, and Ocean Ecosystem (PACE) mission], this approach can be used to similarly assess future sensor performance. Perhaps more importantly, in depth analysis of angular dependence on satellite measurements is required for geostationary satellite design [e.g., the Geostationary Coastal and Air Pollution Events (GEO-CAPE) mission, Fishman et al., 2012], for which targets are only viewed from fixed SZAs. By accounting for (or avoiding) disagreement between satellite sensors, continuous multi-sensor environmental data records may be created and used to address critical science questions on time scales that exceed any individual sensor (e.g., climate variability). Therefore, the goal of this study is to provide a thorough and critical assessment of multi-sensor consistency for a variety of data products, with a focus on changes associated with SZA dependence.

2. Methods

Currently there are numerous methods employed to process satellite ocean color data, yet the most commonly used data products are distributed by the OBPG at NASA Goddard Space Flight Center (GSFC), who provide raw satellite data, processing software, and global Level 3 composites (e.g., monthly) at resolutions ranging from 4 km to 9 km. These data have undergone several rounds of reprocessing to incorporate updates in sensor calibration and algorithm development. Although different from the specific procedures used in creation of Level 3 composites (see Campbell, Blaisdell, & Darzi, 1995), the methods described below generally emulate the approach (e.g., 60° SZA threshold), while allowing for creation of non-standard products (especially SZA).

Level 2 ocean color data from SeaWiFS (1997–2010), MODIS-A (2002–2014), and VIIRS (2012–2014) covering the northern Gulf of Mexico were downloaded from NASA GSFC (oceancolor.gsfc.nasa.gov). These data correspond to processing versions 2010.0, 2013.1, and 2014.0 for SeaWiFS, MODIS-A, and VIIRS, respectively. At the time of writing, these are the most current Level 2 data available. These data were mapped to an equidistant cylindrical projection at 1 km spatial resolution with the bounds 24–31N and 98–79W. Only ocean color bands with corresponding band centers between the three satellites were considered for analysis. Specifically, these include 412, 443, 490, 555, and 670 nm for SeaWiFS, 412, 443, 488, 547, and 667 nm for MODIS, and 410, 443, 486, 551, and 671 nm for VIIRS. For simplicity, in this work the MODIS wavelengths were used to refer to corresponding bands for all satellites (except after scaling the green band, see below).

From the mapped Rrs, several standard and non-standard products were created, including Chl derived using the standard CHLcx algorithm (mg m⁻³; O'Reilly et al., 2000) and the CHLcx algorithm (mg m⁻³; Hu, Lee, & Franz, 2012), total absorption and backscattering coefficients (a Chl, b Chl) derived using the Quasi-Analytic Algorithm (QAA; Lee, Carder, & Arnone, 2002; Lee, Lubac, Werdel, & Arnone, 2009), and diffuse attenuation coefficient for downwelling irradiance (Kd, m⁻¹).
calculated using the $K_{a,lee}$ algorithm (Lee et al., 2005a; Lee, Du, & Arnone, 2005b).

Since SZA is not included among the standard Level 2 products, it was calculated from the Level 2 pixel number (for MODIS and VIIRS) or using the orbital position vectors and target geographic locations (for SeaWiFS). SZA calculated from these approaches was within 0.5° of that calculated from lower level data using the SeaDAS software. SZA data were then mapped to the same projection as the $R_{vis}$ data.

The mapped 1 km resolution products were subsampled to 3 km resolution. During this subsampling, 3 km pixels were excluded from further analysis if (a) the coefficient of variation for the 9 component 1 km pixels exceeded 0.1, (b) any of the 9 component pixels were identified by one or more of the Level 2 processing flags listed in Table 1 (see Patt et al., 2003), or (c) any of the 9 component pixels was deemed optically shallow (depth $< 30$ m for certain regions, see Barnes et al., 2013; Barnes et al., 2014). The L2 flags used are the same as those employed by NASA OBPG for global Level-3 products (minus flag 10, COCCOLITH: Coccolithoforae detected). This quality assurance procedure was performed on all 5 $R_{vis}$ bands (412, 443, 488, 547, and 667), and pixels were only included in further analyses if the data from all bands met the above criteria. Green band $R_{vis}$ (547 nm for MODIS, 551 nm for VIIRS) were scaled to match SeaWiFS (555 nm) according to:

$$ R_{vis}(555) = 10^{a_2} \times \log(R_{vis} - b_2) \quad \text{for} \quad R_{vis} < s_w $$$$ R_{vis}(555) = a_2 \times R_{vis} - b_2 \quad \text{for} \quad R_{vis} \geq s_w $$

where $\lambda$ is the band center of the input green band and the coefficients for MODIS (VIIRS) are $s_w = 0.001723$ (0.001597), $a_1 = 0.986$ (0.988), $b_1 = 0.081495$ (0.062195), $a_2 = 1.031$ (1.014), $b_2 = 0.000216$ (0.000128). These conversions were derived using field-measured hyperspectral $R_{vis}$ from the NOMAD dataset by the NASA OBPG (Bryan Franz, personal comm.). Although other band shift corrections have been employed (e.g. Ménin & Slep, 2015), this conversion is the same as that used in SeaDAS to convert green bands to 555 nm prior to the calculation of ChlOCT. Band shifts for the other wavebands were not corrected, as the modulation due to the band center differences is negligible.

Individual (3 km) pixel data (i.e., all 5 $R_{vis}$ bands, derived products and SZA) were then extracted for every location in the mapped image for every satellite pass. In total, 9.076 SeaWiFS, 6.777 MODISA, and 1.257 VIIRS $R_{vis}$ pixels met the above criteria and were used in subsequent analyses. Fig. 2 (a-c) shows histograms of the relative quantity of data according to geographic position, which did not differ greatly by satellite. Collocated and concurrent (within 1 h) matchups between (1) SeaWiFS and MODIS (hereafter termed ‘SeaWiFS/MODIS’) and (2) MODIS and VIIRS (‘MODIS/VIIRS’) were further extracted, of which there were 1.7e7 and 0.7e7 matchups, respectively.

These data were separated into high Chla (CHLOCT $> 0.25$) and low Chla (CHLOCT $\leq 0.25$) groups, which were analyzed independently. This threshold has been used to designate clear water since the 1980s (Gordon & Clark, 1981), and it is the threshold for CHLOCT transition to CHLCx (Hu et al., 2012). For matchup data, the MODIS CHLOCT record was used to separate the groups. Fig. 3 shows a spatial representation of the frequency of pixels in the low Chla condition.

Finally, data were partitioned according to SZA in 2° steps. For individual sensor data, basic statistics (mean and standard deviation) were calculated for all data within each SZA step (e.g., Fig. 4). Unbiased percent difference (UPD, %) and mean relative difference (MRD, %) were calculated for matchup data within each SZA category in order to assess agreement and bias between sensors:

$$ \text{UPD(%) = } \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - x_i}{0.5 \times (y_i + x_i)} \right| \times 100. $$

Fig. 3. Spatial frequency for which CHLOCT $\leq 0.25$ (% of all records at each pixel) for (a) SeaWiFS, (b) MODIS, and (c) VIIRS data, as well as (d) SeaWiFS/MODIS and (e) MODIS/VIIRS matchups. Gray indicates no data.

$$ \text{MRD(%) = } \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - x_i}{x_i} \right| \times 100. $$

where $x_i$ is the MODISA measurement at matchup $i$ of N total matchups, and $y_i$ is the corresponding measurement from SeaWiFS or VIIRS. Since MODISA overlaps with the other two sensors, all reported biases (MRD) are relative to the MODISA measurement (Eq. 4). As these analyses require a large quantity of data in each condition to average out uncertainties, SZA conditions which included fewer than 500 matchups ($N < 500$) were excluded from analyses.

### 3. Results

Scene-wide means for individual products show angular dependence which varies by sensor and by product (Fig. 4). In particular, a conspicuous oscillating pattern can be seen for both MODIS and VIIRS data. Other trends can also be observed, including $R_{vis}(555)$ and

![Figure 2](image-url) **Fig. 2.** Spatial histogram of data used in this analysis (shown as percentage of maximum frequency) for (a) SeaWiFS (b) MODIS and (c) VIIRS data, as well as (d) SeaWiFS/MODIS and (e) MODIS/VIIRS matchups. The maximum frequencies for these figures are 1485, 1218, 275, 375, and 169 points, respectively. Gray indicates no data.

![Figure 3](image-url) **Fig. 3.** Spatial frequency for which CHLOCT $\leq 0.25$ (% of all records at each pixel) for (a) SeaWiFS, (b) MODIS, and (c) VIIRS data, as well as (d) SeaWiFS/MODIS and (e) MODIS/VIIRS matchups. Gray indicates no data.

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<th>Flag name</th>
<th>Description</th>
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<td>ATMFAIL</td>
<td>Atmospheric correction failure</td>
</tr>
<tr>
<td>1</td>
<td>LAND</td>
<td>Pixel is over land</td>
</tr>
<tr>
<td>2</td>
<td>HIGLINT</td>
<td>High sun glint detected</td>
</tr>
<tr>
<td>3</td>
<td>HILT</td>
<td>Very high or saturated radiance</td>
</tr>
<tr>
<td>4</td>
<td>HITATZEN</td>
<td>High sensor view zenith angle (&gt; 60°)</td>
</tr>
<tr>
<td>5</td>
<td>STRAYLIGHT</td>
<td>Likely straylight contamination</td>
</tr>
<tr>
<td>6</td>
<td>CLDICE</td>
<td>Probable cloud or ice contamination</td>
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<td>7</td>
<td>HISOLZEN</td>
<td>High solar zenith angle</td>
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<td>8</td>
<td>LOWLW</td>
<td>Low water-leaving radiance</td>
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<td>9</td>
<td>CHLFAIL</td>
<td>Failure to derive Chla product</td>
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<td>NAVWARN</td>
<td>Reduced navigation quality</td>
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<tr>
<td>11</td>
<td>MAXAERITER</td>
<td>Aerosol iterations exceed maximum allowable</td>
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<td>CHLWARN</td>
<td>Derived Chla product quality is reduced</td>
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<td>FILTER</td>
<td>User-defined</td>
</tr>
</tbody>
</table>

### Table 1

Level 2 processing flags. Pixels associated with any of these flags were discarded in the analyses.

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*Note: Table content and formatting are placeholders and require actual data to be filled in.*
$R_{rs}(667)$ peaks at approximately 10–20° SZA for MODIS and VIIRS summertime data, high SeaWiFS $R_{rs}(\lambda)$ at 20° (and to a lesser extent, 60°) SZA, as well as larger overarching trends, both increasing (e.g., MODIS $R_{rs}(412)$) or decreasing (e.g., VIIRS summertime $R_{rs}(488)$, MODIS and VIIRS CHL$_{oce}$, and MODIS CHL$_{cl}$. Fig. 5 shows mean CHL$_{oce}$ in 10° SZA bins (removing the higher frequency oscillating pattern) as a function of time, highlighting angular dependence of this product, especially for MODIS data.

Fig. 3 shows that the majority of locations in this scene, especially offshore waters, are typically classified as low Chla (MODIS CHL$_{oce}$ ≤ 0.25), while the largest distribution of valid data was seen on the West Florida Shelf (WFS, Fig. 2). More importantly, however, only minor differences are seen between sensors on these measures, indicating comparability between sensors. Indeed, the matchup datasets also show similar spatial patterns to the single sensor datasets in data distribution and low Chla occurrence (Figs. 2d–e, 3d–e).

The distribution of matchup data according to sensor zenith shows patterns expected given individual satellite characteristics (Fig. 6). SeaWiFS and MODIS pixels are spatially larger for higher SZA, thus mapped products show a general increase in mapped data quantity (and thus more matchups) at larger zenith angles (Fig. 2a). VIIRS pixels are also spatially larger at higher SZA, however the pattern of increased mapped data quantity with SZA is obscured in the MODIS/VIIRS dataset (Fig. 6b) due to similarities in the satellite orbits (Fig. 1b). Due to tilting of the sensor (to avoid sun glint), nearly all SeaWiFS data have a SZA > 20°. For subsequent analyses, data with SZA < 20° are
ignored. The high quantity of data for SeaWiFS SZA ~ 22–26° is also an artifact of the sensor tilting, as SeaWiFS SZA with pixel number is parabolic in shape.

Figs. 7 and 8 show UPD by SZA for matchups of various products, from both low- and high-Chla subsets. Overall, the UPD between SeaWiFS/MODIS and MODIS/VIIRS $R_{rs}$ measurements show very similar patterns and magnitudes. For SeaWiFS/MODIS matchups, UPD tends to slightly increase with increasing SeaWiFS SZA (Fig. 7), but shows little dependence on MODIS SZA. Conversely, UPD increases are seen both with increasing MODIS and VIIRS SZA (Fig. 8), although this effect is not uniform across all $R_{rs}$ bands. For both sensor comparisons, agreement between blue bands is better for low Chla waters, however the opposite is true for green and red bands. MRD is generally positive for SeaWiFS/MODIS and negative for MODIS/VIIRS $R_{rs}$ measurements, indicating that, on average, SeaWiFS $R_{rs} <$ MODIS $R_{rs} <$ VIIRS $R_{rs}$. Although not shown in Figs. 7 & 8, $R_{rs}(443)$ shows patterns that are intermediate between those of $R_{rs}(412)$ and $R_{rs}(488)$. Also not shown, $R_{rs}(667)$ shows high UPD between satellites, generally above 20% for all SZA due to the low $R_{rs}$ values, especially in low Chla waters. UPD and MRD encompassing the complete matchup datasets (i.e., not partitioned by SZA) are displayed for all products tested in Table 2.

Comparison between the Chla algorithms tested (Fig. 9) indicate greatly improved agreement between sensors for the CHLOCI algorithm relative to the CHLOCx algorithm. Nevertheless, UPD and MRD increases can be seen with increasing MODIS SZA, especially for the MODIS/VIIRS comparison. These products show nearly identical patterns for the high Chla waters (not shown), which is expected given that the CHLOCI product transitions to using CHLOCx data when CHLOCI $N < 0.25$ mg m$^{-3}$. Nevertheless, there is some slight degradation (increase in UPD) in the CHLOCI product for high Chla waters (Table 2).

Finally, sensor disagreement in $R_{rs}$ products are not directly propagated to QAA or $K_{d}$,lee products (Fig. 10). In fact, with the exception of 488 nm data, $a_{q}$ and $K_{d}$ generally show UPD reduced in magnitude relative to the corresponding $R_{rs}$ band. UPD for the $b_{n}$ product is on par with the corresponding $R_{rs}$ band, but does not seem to greatly affect $K_{d}$ calculation. Interestingly, however, a pronounced (relative to the input $R_{rs}$) dependence on MODIS SZA can be observed for many of these products.

4. Discussion

Overall, this study demonstrates generally high cross-sensor fidelity for both $R_{rs}$ and derived products. This is similar to that seen for other satellite/satellite comparisons (Franz et al., 2005, 2012; Barnes & Hu, 2015), and reflects strong performance of these sensors, the atmospheric correction, ongoing calibration efforts, and the algorithms used to derive geophysical products. Nevertheless, clear degradation of this...
fidelity is observed according to SZA for individual sensors as well as their matchups.

Single sensor data shows angular dependence (Fig. 4), as ideally there should be no change in the scene-wide mean of any product as a function of SZA. A portion of this angular dependence, however, can be attributed to specific characteristics of the study region. In particular, the oscillating pattern observed in the scene-wide mean of certain MODIS and VIIRS products (e.g., Fig. 4a,e,f) results from a coincidental alignment of the satellite orbit tracks (Fig. 1) relative to the orientation of Florida. Because MODIS and VIIRS strictly repeat their orbital paths, data at a specific SZA view certain targets repeatedly (Fig. 11) to the exclusion of others. The result is that scene-wide means determined with high SZA-restricted datasets actually represent means of different combinations of locations. This effect is compounded by high relative density of valid data on the western and eastern coasts of Florida (Fig. 2) as well as the high Chla (compared to the majority of the scene) near Florida, resulting in the oscillating patterns seen.

These oscillating patterns largely disappear when considering only offshore data (e.g., 24 N–27 N, 94–85 W; Fig. 12), indicating that they are indeed related to the specific geography of the entire scene. Nevertheless, these patterns provide insight into potential issues relating to SZA, especially that any given location is only viewed at a small number of SZAs (approximately 6 for MODIS and VIIRS). As such, other SZAdependent patterns in scene-wide means [e.g., the large decline in mean MODIS \( R_{rs}(667) \) from ~10° to 60° SZA; Fig. 4d] will affect certain locations disproportionately. Products derived using these wavebands will also be affected, easily apparent in time series partitioned by SZA (Fig. 5). In total, angular dependence of measurements for a single sensor can have implications for retrievals from specific targets (e.g., time series at virtual buoy locations, Hu & Le, 2014), and can also affect means and time series for larger scenes (Fig. 5). For SeaWiFS, angular dependence does not have this geographic component, as the orbit was much more irregular (although the orbital drift was minor for the first few years of deployment, (Eplee et al., 2012b)).

The single sensor datasets also indicate prominent summertime peaks in mean \( R_{rs} \) data for MODIS and VIIRS around 15–20° SZA (Fig. 12a,b,c,d). These peaks are not seen in wintertime data, indicating potential glint contamination. However, similar trends are seen in SeaWiFS \( R_{rs} \) at these bands, which should not suffer from glint contamination due to the tilting of the sensor. Indeed, most SeaWiFS \( R_{rs} \) bands show high means at low (~20–30°) and high (~55–60°) SZA, both in summer and winter. As such, these trends may result from residual BRDF correction uncertainties. While the CHLCX product (which is based on a ratio between 555 nm data and 443, 488, or 510 nm) propagates this angular dependence, the CHLOCX product (based on subtractions between 443, 555, and 667 nm data) is largely resilient to these across-the-board increases.

In addition to the general trends listed in the results section, some nuanced differences in angular dependence by products are also apparent. For both single sensor and matchup datasets, differences in band-specific \( R_{rs} \) angular dependence can be important in explaining SZA dependence for derived products. For example, SeaWiFS/MODIS matchups

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**Table 2**

Summary of UPD and MRD for SeaWiFS/MODIS (S/M) and MODIS/VIIRS (M/V) matchups according to product. \( a(\lambda) \) and \( b(\lambda) \) are derived from the QAA, while \( K_d(\lambda) \) is from the Kd_lee algorithm (Lee et al., 2002; Lee et al., 2005a; Lee et al., 2005b).

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<td>10</td>
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<tr>
<td>Rs(555)</td>
<td>9</td>
<td>5</td>
<td>8</td>
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<td>Rs(667)</td>
<td>42</td>
<td>37</td>
<td>25</td>
<td>20</td>
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<td>Rs(412)</td>
<td>29</td>
<td>25</td>
<td>17</td>
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<td>Rs(488)</td>
<td>18</td>
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<td>Rs(555)</td>
<td>29</td>
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**Fig. 8.** Same as Fig. 7, but with MODIS/VIIRS matchups.
show UPD increases as SeaWiFS SZA increases for all \( R_{rs} \) bands (Fig. 7). Similar to the SeaWiFS example above, the band ratio product (\( \text{CHLOCx} \), Fig. 9a) shows dependence on SeaWiFS SZA, while the subtraction algorithm (\( \text{CHLOCI} \), Fig. 9b) is resilient to the across-the-board increases in \( R_{rs} \) uncertainty according to SeaWiFS SZA. However, in addition to the increases in \( R_{rs} \) uncertainty with increasing SeaWiFS SZA (Fig. 7c), \( R_{rs}(555) \) (Fig. 7c) and \( R_{rs}(667) \) (not shown) also display increased UPD at high MODIS SZA which is not seen for other bands. As such, both \( \text{CHLOCx} \) and \( \text{CHLOCI} \) (Fig. 9a,b) show angular dependence on MODIS SZA, although the latter is much reduced. A similar effect can be seen in MODIS/VIIRS matchups, where \( R_{rs}(412) \) (Fig. 8a, d) and \( R_{rs}(443) \) (not shown) indicate UPD increases as both SZAs increase, yet \( R_{rs}(488) \) (Fig. 8b, e) and \( R_{rs}(555) \) (Fig. 8c, f), especially in the high \( \text{Chla} \) condition (Fig. 8e, f), show discrepancies mostly associated with

**Fig. 9.** Unbiased percent difference (UPD, %) between SeaWiFS/MODIS (top row) and MODIS/VIIRS (bottom row) \( \text{CHLOCx} \) (left column) and \( \text{CHLOCI} \) (right column) matchups. Only low Chla (MODIS ChloCx \( \leq 0.25 \) mg m\(^{-3}\), top row) data are shown. Symbols (+ and -) represent direction of bias (mean relative difference, MRD), where MRD > 10% (bold) or 5 < MRD < 10% (non-bold).

**Fig. 10.** Unbiased percent difference (UPD, %) between \( \alpha_{s}(488) \) (left column), \( b_{p}(488) \) (center column), and \( K_d(488) \) (right column) for SeaWiFS/MODIS (top row) and MODIS/VIIRS (bottom row) matchups. Only low Chla (MODIS ChloCx \( \leq 0.25 \) mg m\(^{-3}\)) data are shown. Symbols (+ and -) represent direction of bias (mean relative difference, MRD), where MRD > 10% (bold) or 5 < MRD < 10% (non-bold).
increases in VIIRS SZA. Again, while CHLOCI and CHLOCx show UPD increases with MODIS SZA, CHLOCI is resilient to the larger uncertainties at high VIIRS SZA (Fig. 9d).

The uncertainties seen in $R_{rs}$ data are also not directly propagated to QAA or $K_{d}$ products (Fig. 10). As the QAA is semi-analytical (i.e., not based on simple ratios or band subtraction), it is more difficult to relate observed SZA dependence to that of input $R_{rs}$ bands. The QAA uses the 443, 490, 555, and 667 nm $R_{rs}$ data to calculate products which are subsequently applied to $R_{rs}(\lambda)$ for any band for $a_{\lambda}(\lambda)$ and $b_{\lambda}(\lambda)$ derivation (Lee et al., 2002, 2009). With the exception of 488 nm products, the resulting $q_{\lambda}(\lambda)$ shows better cross-sensor agreement than the input $R_{rs}(\lambda)$ (Table 2). For MODIS/SeaWiFS matchups, dependence on MODIS SZA (Fig. 10) is likely introduced through angular dependence in MODIS $R_{rs}(555)$ and $R_{rs}(667)$ UPD. Although $b_{\lambda}(\lambda)$ is used in $K_{d,\lambda}$ calculation, $K_{d,\lambda}(\lambda)$ shows angular dependence similar to that for $a_{\lambda}(\lambda)$ because $a_{\lambda}(\lambda) > b_{\lambda}(\lambda)$ for most waters in the study region. It is likely that the $K_{d,\lambda}/QAA$ modification optimized for optically shallow water (Barnes et al., 2013), which relies more heavily on 667 nm data, would show larger SZA dependence and cross-sensor disagreement, commiserate with those reported for $R_{rs}(667)$.

4.1. Implications and future research needs

As shown, the etiology for angular dependence of derived products in these satellite/satellite comparisons can often be determined from SZA-dependent UPD changes in the input $R_{rs}$ (e.g., Figs. 7 & 8) in combination with fluctuations in scene-wide means for single sensors (e.g., Fig. 12). Analysis on a more broad scale (across products and including all three sensors), however, also can reveal important findings. For example, Fig. 12 shows much improved performance of the CHLOCI product (Fig. 12f) relative to CHLOCx (Fig. 12e), demonstrated through less angular dependence (ignoring the geographically-based oscillating patterns) as well as increased cross-sensor agreement. In recent reprocessings, NASA OBPG has switched from CHLOCx to CHLOCI as its default Chla product for clear waters, and this finding adds to the justification for that transition. However, Fig. 5 highlights residual angular dependence of this product which may need to be addressed. Furthermore, reduced agreement between sensors in the high Chla datasets (Table 2) indicates that transition from OCI- to OCx-derived Chla (which occurs from 0.25 to 0.3 mg m$^{-3}$ in the CHLOCI product) may need to be revisited.

In light of the lack of angular dependence (except at very high MODIS SZA) for CHLOCI derivations for the SeaWiFS/MODIS matchup comparison (Fig. 9b), it is perplexing to see disagreement between MODIS and VIIRS for MODIS SZA $\sim 40^\circ$ (Fig. 9d). Transitive logic would dictate that if SeaWiFS and MODIS agree (and thus are likely correct), then differences between MODIS and VIIRS, if present, should manifest according to VIIRS (not MODIS) SZA. It is possible that MODIS sensor degradation between its overlap with SeaWiFS (ended in 2010) and VIIRS (began in 2012) contributes to this phenomenon. Indeed, Fig. 5 indicates that the MODIS CHLOCI angular dependence has

Fig. 11. Similar to Fig. 2, spatial histogram of data (percentage of maximum frequency) for MODIS data with SZA range (a) 18–22° and (b) 24–28°. Maximum frequencies are 187 and 175, respectively.

Fig. 12. Same as Fig. 4, but with data restricted to offshore waters only (24–27 N, 94–85 W).
perhaps increased during these two time periods, but this change is not statistically significant (one-tailed Student’s T-test, p = 0.11).

As with any such analyses, the dataset (and thus findings) could be biased by the study design. In particular, the time difference allowed between satellite measurements to be considered matchups (1 h), the coefficient of variation (CV = 0.1) employed, the spatial resolution (3 km), and the handling pixels determined as questionable by the Level 2 processing flags could all impact the values reported here. Nevertheless, Barnes and Hu (2015) found variation due to such factors to be relatively minor. For convenience, sample times were determined from the GSFC granule filenames, but this convention ignores satellite-specific variation in granule duration (~20 min for SeaWiFS, 5 min for MODIS, ~1.5 min for VIIRS). As such, SeaWiFS/MODIS matchups are within ~85 min while MODIS/VIIRS matchups can only differ by ~67 min. Given the spatial resolution of this study and the multi-year aggregation of data, it is unlikely that this difference greatly impacts the findings presented here.

The single sensor analyses highlight several examples of angular dependence of both \( R_s \) and derived geophysical products from SeaWiFS, MODIS, and VIIRS individually. Such findings, however, are potentially contaminated by the specific characteristics of this study region (see Fig. 4 vs Fig. 12).

Additionally, displaying only the means (i.e., without statistical analyses) for this spatially and temporally variable region might seem somewhat disingenuous, as the standard deviations around these means can encompass the observed trends and variability between sensors. As such, repeat of these analyses for more spatially and temporally consistent waters (e.g., ocean gyres) may provide increased statistical confidence in the observed trends, although the preponderance of clouds in such environments might reduce data quality enough to offset this statistical benefit. It is important to note, however, that the study region is representative of other regions around the globe that include coastal and offshore waters. The Gulf of Mexico region, specifically, has been extensively studied using satellite ocean color data for many years (Muller-Karger, Walsh, Meyers, & Evans, 1991; Stumpf, 2001; Hu et al., 2003, 2011; Hu, Barnes, Qi, & Corcoran, 2015; Gower, Hu, Borstad, & King, 2006), thus characterization of the uncertainty and errors in these measurements is critical. Furthermore, the trends observed in this work show consistency (or deviation) as generally expected across years (e.g., Fig. 5), wavebands, seasons, \( Chla \) regimes, and sensors (Figs. 4 and 12), increasing confidence in their robustness. Finally, the analyses of satellite/satellite matchups demonstrate another approach of rigorous assessment of satellite uncertainties and supplement the findings for single sensor datasets using field-measured data.

Together, these analyses are intended to improve understanding of angular dependence in satellite ocean color measurements, with direct applicability towards assessment of single- and cross-sensor consistency. Account of these differences is essential for long-term data continuity. Specifically, highest quality \( R_s \) data is restricted to SZAs less than 40–50° for SeaWiFS, MODIS, and VIIRS, thus satellite/in situ calibration and validation efforts might be improved by excluding high SZA data. The cost of such exclusion, however, would be a large portion of the data (Fig. 6). Alternatively, potential remediation of this angular dependence (e.g., Meister & Franz, 2014) would greatly improve accuracy of single sensors and continuity of multi-sensor datasets. Finally, the results presented here will also be useful in interpreting data product quality from geo-stationary platforms (e.g., GEO-CAPE, Fishman et al., 2012) as any target will be viewed at a fixed SZA. Data quality across variable SZAs from such platforms can be compared with those listed here to diagnose whether there might be other factors than the SZA dependence that could contribute to data product uncertainties.

5. Conclusions

This study revisits the work of Barnes and Hu (2015) with emphasis of angular dependence in single sensor measurements and cross sensor consistency. The findings presented here show generally strong continuity of \( R_s \) measurements and derived products, while also highlighting several instances of degradation according to viewing geometry. Together, these analyses demonstrate clear differences between derived products with respect to angular dependence, and highlight the need to remove data (or, at least, account for uncertainties) at larger SZAs. Nevertheless, there is no clear propagation of SZA-related uncertainties to certain derived products, as some algorithms seem to be resilient to at least some of the \( R_s \) angular dependence. These findings also have implications for design and calibration of geostationary ocean color sensors, for which targets are only viewed at fixed sensor zenith.

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