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# Remote Sensing and Water Quality Indicators in the Korean West Coast: Spatio-temporal Structures of MODIS-derived Chlorophyll-a and Total Suspended Solids

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**ABSTRACT**

The Yellow Sea is a shallow marginal sea with a large tidal range. In this study, ten areas located along the western coast of the Korean Peninsula are investigated with respect to remotely sensed water quality indicators derived from NASA MODIS aboard of the satellite Aqua. We found that there was a strong seasonal trend with spatial heterogeneity. In specific, a strong six-month phase-lag was found between chlorophyll-a and total suspended solid owing to their inversed seasonality, which could be explained by different dynamics and environmental settings. Chlorophyll-a concentration seemed to be dominantly influenced by temperature, while total suspended solid was largely governed by local tidal forcing and bottom topography. This study demonstrated the potential and applicability of satellite products in coastal management, and highlighted find that remote-sensing would be a promising tool in resolving orthogonality of large spatio-temporal scale variabilities when combining with proper time series analyses.

**Keywords:** Chlorophyll-a, Suspended solids, Surface temperature, Remote sensing, Yellow Sea

Coastal environments throughout the world are now experiencing unprecedented anthropogenic eutrophication, hypoxia and harmful algal blooms due to increased human activities and subsequently increased nutrient loadings (Anderson et al., 2002; Diaz and Rosenberg, 2008). Because of their significant role in human well-being relying upon them, deterioration of water quality indicators (e.g., water temperature, dissolved oxygen, chlorophyll, inorganic nutrients, heavy metals, total suspended solid, etc.) can be potentially catastrophic for marine ecosystems as species are threatened by conditions which are no longer suitable for their survival (Bierman et al., 2011). As a result, monitoring changes in spatio-temporal patterns of water quality (WQ) in both terrestrial and marine ecosystems, and interpretation of the implications have been important across disciplines these days, such as environmental/marine sciences and socio-economics. However, it is inherently difficult to properly address varying spatial and temporal scales of WQ for application to coastal marine waters monitoring and assessment (Bierman et al., 2011).

Recently, the application of satellite and airborne remote sensing imagery to collect WQ information has become more frequent (Goetz et al., 2008). Remotely sensed datasets are generally more comprehensive than those directly measured *in situ* in that they provide greater spatial coverage with finer resolution and often increased temporal frequency and resolution. This makes remote-sensing approach a rich source of data. However, the large amount of data also embeds challenges for the extraction of meaningful information of WQ parameters. Remotely-sensed sea surface temperature (SST) is one of the most important oceanic and atmospheric variables which has been widely used in a variety of researches to develop an understanding of ocean dynamics, as well as physical and biogeochemical processes in the upper ocean (Park et al., 2015). For example, the year-to-year variations of SST in the Yellow Sea (YS) may significantly affect the Korean, Chinese and Japanese climate, and thus it is important to examine the characteristic variability of SST, which may help assess the climate variability and its down-scaled impacts over the YS and adjacent countries (Yeh and Kim, 2010).

The global distribution of chlorophyll-a (Chl-a), the direct proxy for phytoplankton biomass (Cullen, 1982), shows Chl-a rich regions located along the coasts and continental shelves, mostly because of a strong nutrient supply from continents. The visualization of satellite images is the primary technique used to identify their presence, in particular when phytoplankton blooms occur as a regular event in a specific ocean region (Srokosz and Quartly, 2013), or in regions where they are not usually expected such as oligotrophic gyres in North Pacific (Wilson, 2003; Wilson et al., 2008). During the last decade, there has been an increase in peer-reviewed publications on the study of algal blooms using ocean color satellite data (Blondeau-Patisseier et al., 2014). Algal blooms in coastal ocean regions have mainly been the primary focus of those studies mostly because of the direct connectivity between land and coastal waters (Gazeau et al., 2004). Additionally, the second and third generation development of satellite ocean color sensors allowed more accurate retrieval of phytoplankton proxies in coastal waters (Shen et al., 2012).

Recent reviews on satellite ocean color remote sensing have reported on the scientific advances, societal benefits (IOCCG, 2008) and applications to coastal ecosystem management (Kratzer et al., 2014; Klemas, 2011), including fisheries (Wilson, 2011) and harmful algal blooms detection (Shen et al., 2012). These ocean color datasets allow for the derivation of ecological baselines which can then be used to detect and anticipate changes in the ocean systems' dynamics (Siegel et al., 2013; Wong et al., 2009; Smetacek and Cloern, 2008). Archived earth observation data can be used in hindsight to assess prevailing bloom conditions and to identify biological and physical parameters that triggered or terminated an algal event (Kahru et al., 1993).

In coastal waters, total suspended solid (TSS) can be an important factor controlling biological processes (Doxaran et al., 2003) and its distribution and variations can be strongly influenced by tides and river discharge (Stumpf and Pennock, 1989; Son et al., 2014; Kim et al., 2014). TSS is also important in light penetration and water movements in the coastal waters (Son et al., 2014). Thus, accurate estimation of TSS is critical to understand the thermal structure of upper water columns and physical processes (Lewis et al., 1990; Morel and Antoine, 1994; Sathyendranath et al., 1991) as well as biological processes (e.g., phytoplankton photosynthesis) in the ocean euphotic zone (Platt et al., 1988; Sathyendranath et al., 1989).

There have been extensive studies on spatial and temporal distribution of SST, Chl-a, and TSS both in the offshore and coastal regions of the YS (Park and Oh, 2000; Xie et al., 2002; Ahn et al., 2004; Chu et al., 2005; Yeh and Kim, 2010; Wei et al., 2010; Lee et al., 2013; Son et al., 2014; Park et al., 2015;). None of the studies, however, attempt to address these three components combined with respect to the interactive dynamics between them, and few studies have compared WQ data derived from satellite with *in situ* monitoring data. The research objectives of this paper include: 1) examining spatial and temporal variability of SST, Chl-a and TSS in the YS; 2) ground-truthing of satellite data based on long-term monitoring data *in situ*, 3) presenting applicability of satellite-based SST, Chl-a and TSS data with better descriptions of spatio-temporal patterns over larger areas of the YS to WQ management.

The Yellow Sea (YS) is a marginal sea with shallow depth (c.a. 44m; Wei et al., 2010) and large tidal range reaching up to 10m (Choi and Kim, 2006). In the present study, 10 regions in Korean west coast (KWC), where satellite data were acquired, are delineated by bays and river discharges as follows (Fig. 1): Gyeonggi Bay (A1); Asan Bay (A2); Taean Coast (A3); Cheonsu Bay (A4); Boryeong Coast (A5); Seocheon Coast (A6); Saemangeum Dike (A7); Gochang Coast (A8); Mokpo Bay (A9); and Wando Coast (A10). Geographical coordinates of delineated boundaries of each are listed in Table S1.

To provide spatial distribution and temporal trends of WQ in the study area, SST, Chl-a, TSS of surface waters were analyzed based on the *in situ* data provided by Marine Environmental Monitoring System of Korea (K-MEMS). As for the purpose of regional comparison, 10 regions are allocated along KWC (Fig. 1). Han River estuary was set as a northern limit and Wando Coast as a southern limit of the boundary. K-MEMS has been seasonally monitoring SST, Chl-a and TSS at a total of 105 stations in the study area since 1997 to the present.

The ocean color and sea surface temperature data from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) on the satellite Aqua are available from the NASA's Ocean Color website (http://oceancolor.gsfc.nasa.gov/) supported by the Ocean Biology Processing Group (OBPG) at NASA's Goddard Space Flight Center. MODIS-Aqua Level-2 daily ocean color products such as Chl-a and remote sensing reflectance ($R_{rs}$) at various wavelengths ($R_{rs}(\lambda)$), and day time SST covering the KWC waters (Fig. 1) were obtained from the NASA ocean color website for the period of July 2002 to December 2014. The MODIS-Aqua level-2 ocean color data were derived using the standard atmospheric correction algorithm with the near infrared (NIR) radiance corrections (Bailey et al., 2010; Stumpf et al., 2003). The MODIS Chl-a data are derived using the NASA standard ocean color chlorophyll algorithm for MODIS (OC3M) (O'Reilly et al., 2000). The day time MODIS SST product from the NASA OBPG are derived using the long-wave SST algorithm with MODIS bands at 11 and 12 μm (Minnett et al., 2004). More information about the MODIS-Aqua Level-2 data can be found at the OBPG website (http://oceancolor.gsfc.nasa.gov/WIKI/OCReproc2013(2e)0MA.html). Those Level-2 data were remapped to a standard Mercator projection at 1 × 1 km spatial resolution for the study area.

The regional TSS model (Siswanto et al., 2011; Son et al., 2014) using $R_{rs}$ at 3 wavelengths (488, 547, and 667 nm) were applied to the remapped daily MODIS-Aqua data to generate TSS maps in KWC as follows:

$$Log(TSS) = 0.649 + 25.623 \cdot [R_{rs}(555) + R_{rs}(670)] - 0.646 \cdot \frac{R_{rs}(490)}{R_{rs}(555)} \quad (1)$$

Monthly and climatology monthly composite SST, Chl-a, and TSS images were generated using the daily MODIS-derived products to characterize spatial and temporal variation of SST, Chl-a, and TSS in the Yellow and East China Seas. Time series of a long-term climatology (mean distribution of all months from July 2002 to December 2014) and monthly climatological images (12-year mean for each month) of SST, Chl-a and TSS from the MODIS-Aqua data were generated for the 10 study regions (Fig. 1 and Table S1).

In this study, authors used MODIS-derived data set from the 10 regions to decompose into principal components to examine spatio-temporal structure of Chl-a and TSS. In general, empirical orthogonal function (EOF) is used to analyze spatial structure by decomposing of spatial multivariate data. EOF analysis is a principal component analysis (PCA) applied to a group of time series over a certain spatial range, such as multiple points or 2-D field data sets. A new time series of coherent variations (a.k.a., scores) was created from original time series and eigenvectors of covariance matrix (a.k.a., loadings) from EOF analysis. The time series of coherent variation for the major principal component (PC1 or EOF mode 1 explaining temporal pattern) was then filtered removing seasonality in order to focus on inter-annual variability and was compared using cross-spectral analysis to compute lags between the two time series.

After seasonality removed, filtered time series of coherent variation (i.e., scores) for the major principal component (PC1 or EOF mode 1) from Chl-a time series was compared against NIÑO3.4, which is a representative climate index for one of El Niño Southern Oscillation (ENSO) indices. The NIÑO3.4 is defined by mean SST over the region of 5° S - 5° N and 170° W - 120° W. It has been reported that this is a region of great climate variability in ENSO time scale and has proximity to the area where there is important effect in shifted SST on the precipitation patterns over a large region in the western Pacific Ocean (Trenberth, 1997). Monthly NIÑO3.4 data (version ERSST.V3B;

www.cpc.ncep.noaa.gov/data/indices/) were obtained from the Climate Prediction Center (CPC) of National Centers for Environmental Prediction (NCEP) at National Oceanic and Atmospheric Administration (NOAA).

A cross-correlation (XCF) analysis was also performed over the long-term time series of MODIS-derived monthly Chl-a and TSS. Cross-correlation analysis is a statistical method in finding how far any two time series are apart (i.e., time lags) and how strong cross spectral power they have (signs determine if the two time series are positively or negatively correlated). Cross spectral power gives frequencies of the two time series and cross-correlation coefficients are the indicator of the lag where the two time series are best aligned. Therefore, if the two time series have the same frequency with a phase-lag, the cross spectrum of the two series will yield the same spectral power structure that each individual time series reveals.

Long-term climatology imageries of MODIS-derived SST, Chl-a, and TSS from all months during the period of July 2002 through December 2014 are presented for the Korean west coastal waters to provide mean spatial patterns (Fig. 2). Overall, SST increases toward the south in general (Fig. 2a). Relatively lower SST appears over the A1 (Gyeonggi Bay) due to strong tidal currents and shallow bathymetry, while SST is relatively higher around the Wando Coast (A10) although there is strong tidal mixing. Spatial distributions of Chl-a and TSS concentrations reveal somewhat similar patterns that the concentrations are higher along the coasts and lower offshore (Figs. 2b and 2c). However, relatively higher Chl-a values are observed in the southern part of the area A1 (e.g., Lake Sihwa), A4 (Cheonsu Bay) and A7 (Saemangeum Dike), while higher TSS values are dominant over large areas of the A1 (Gyeonggi Bay), A9 (Mokpo Bay) and A10 (Wando Coast) due to their local characteristics, such as shallow bathymetry and strong tidal mixing.

Monthly climatological (2002–2012) images of MODIS-derived SST, Chl-a, and TSS for the KWC are derived (Fig. 3). In general, spatial distributions of the climatological monthly SST, Chl-a, and TSS images are similar to that from the climatology images from July 2002 to December 2014 shown in Fig. 2, and there are strong seasonal variabilities over the entire study areas.

The MODIS-derived SST images show that SST is lower in the coastal waters (lowest in Gyeonggi Bay) while SST is higher offshore waters and southern YS over all months (Fig. 3a). The lower SST along the coasts, especially in Gyeonggi (A1) and Wando Coast (A10) area, is caused by strong vertical mixing due to the tidal currents and shallow bathymetry. Lower SST appears in winter months (with lowest in February with mean SST by about 2°C in A1) and higher SST in summer months (highest in August with mean SST by about 28°C in the entire KWC).

Monthly climatology of the MODIS imageries provides that Chl-a concentrations are higher onshore of the KWC and lower in the middle and south offshore of the YS in most of months (Fig. 3b). However, in the middle of the YS, Chl-a concentrations are higher in spring months (March to May) and autumn (November to December). The highest Chl-a values in April would be related to spring phytoplankton bloom in the middle of the YS. The lowest Chl-a values appear during the summer months in the middle of YS. However, relatively higher Chl-a concentrations are shown in summer season along the KWC (e.g., highest SST values in August from A4 and A7).

General spatial distributions of the MODIS-derived monthly TSS reveal similar patterns to those long-term climatological TSS from 2002 to 2014, showing higher TSS along the KWC (especially, in A1 of Gyeonggi Bay and A10 of Wando Coast area) and lower in offshore (minimum in the middle of the YS) (Fig. 3c). The TSS values are highest in winter (December to March) and lowest in summer months (July to August) in all regions. The maximum TSS values are shown in A1 (Gyeonggi Bay) and A10 (Wando Coast) region (about 10 –12 mg $L^{-1}$ on average) in the winter months. The ribbon-shaped features are always shown in A1 over all months, which is attributed to the tidal asymmetry effect (Jay and Musiak, 1994) because Gyeonggi Bay is under estuarine regime where fresh- and salt-water mixing occurs more actively than other 9 regions (Son et al., 2014).

This section describes the temporal variability of SST, Chl-a, and TSS in each region for the past 10 years (2004-2014), by analyzing both satellite-derived and *in situ* observation data. Figure 4a shows the time series of SST in 10 regions. Red circles represent the data seasonally observed *in situ* observed, while the blue lines are for the MODIS-derived monthly SST. The most striking feature is the seasonal variability of SST, whereby warm during summer and cold during winter. In general, MODIS-derived SST matches very well with the observation data particularly in northern regions (e.g., A1 - A6). In the southern areas (e.g., A7 - A10), the MODIS-derived values tend to slightly overestimate the SST especially during winter, but the discrepancies are not noticeable.

Time-series of Chl-a for each region is plotted in Fig. 4b. When compared to SST, one can note that the discrepancy between the observation and MODIS-derived Chl-a concentrations which are two or three times larger in magnitude than the *in situ* measurements. Overall, the observation data range 0 to 5 μg $L^{-1}$ for most periods other than some spikes. Those spikes occur early spring (February or March) in A1 and A2, which thought to represent early-spring blooming in the coastal areas (Fig. 4a and 4b). Some exceptional cases of these spikes occurring during summer months in A3 - A8 can be found in both observation and MODIS-derived data during 2005-2007 (Fig. 4b). Chl-a concentration in A4 (Cheonsu Bay) shows the highest values out of all 10 regions, which are consistent in both observation and MODIS-derived data. Some of spikes are coherent among regions, but hard to find the trend in spatial coherency. MODIS-derived data overestimate *in situ* Chl-a except for regions of A9 and A10.

Figure 4c depicts the temporal variability of TSS in 10 regions. Similar to the case of Chl-a, there exists discrepancy between *in situ* measurements and MODIS-derived TSS. In general, the MODIS-derived TSS is smaller than the *in situ* measurements with little exception, contrary to Chl-a cases.

An empirical orthogonal function (EOF) analysis (a.k.a., principal component analysis: PCA) is applied to the long-term time series of MODIS-derived monthly Chl-a and TSS data from 10 regions (Fig. 5, 6 and 7). As mentioned earlier, a PCA is a statistical tool to decompose multiple variables into principal components having orthogonality, and these components can be ranked with respect to its contribution that can explain variances of the time series. Eigenvectors of the co-variance matrix from the MODIS-derived Chl-a and TSS at 10 regions are plotted in 2-dimensional X-Y space with X being PC1 and Y being PC2 (Fig. 5a and 5b), respectively. Variance explained by 10 PCs for the same time series data sets are also presented.

It is noteworthy that loadings from both Chl-a and TSS times series are located on the positive axis of PC1 (upper right and lower right quadrant) which represents temporal structure (Fig. 5a and 5b). This indicates that all 10 regions have similar and strong seasonal patterns of Chl-a and TSS and their variances can be significantly explained by PC1 (47.3% and 74.6%, respectively). However, PC2, representing spatial structure, reveals somewhat different features than PC1 has shown. Loadings from each region are clustered into two groups along the PC2 axis (see colored circles grouping 10 regions into two in Fig. 5a and 5b). Bays from the northern part of the YS (A1 and A2) are grouped together with those from the south (A9 and A10) in the positive axis of the PC2 (upper right quadrant) for Chl-a

(Fig. 5a) and negative axis of the PC2 (lower right quadrant) for TSS time series (Fig. 5b), respectively. This indicates that Chl-a and TSS behaviors in the north (A1 and A2) and south (A9 and A10) are different from the rest regions (A3-A7, e.g., Saemangeum Dike and Cheonsu Bay). This synoptic heterogeneity was previously described in the monthly climatological characteristics.

To determine time lags between the two time series, a cross-correlation function (XCF) is applied to the long-term time series of MODIS-derived monthly Chl-a and TSS. Figure 6 presents PC1 (EOF mode 1) from Chl-a time series overlaid by that from the TSS time series. It was found that there is a strongly negative correlation in the PC1 (EOF mode 1) from the two time series (Fig. 6a). This was statistically supported by strongly negative cross spectral power at the frequency of 1 year (Fig. 6b) indicating that both Chl-a and TSS time series have 1-year frequency but their peaks are negatively correlated. The coherence of the 1-year frequency is about 0.85 which was found to be statistically significant ($p<0.05$) within 95% confidence level (Fig. 6c). In this XCF analysis, even if not statistically significant, it was found that there is a 6-month phase-lag between the two PC1 of Chl-a and TSS time series data and the correlation coefficient of this phase-shift is 51% (Fig. 6d). This negative correlation between the two properties was also shown in the PCA data structure in Fig. 5. One can note that these two groups (north and south regions vs. middle regions) reveal inversed relationship between the Chl-a and TSS time series. For example, those regions with positive PC2 (upper right quadrant) of Chl-a are located in the negative side of PC2 (lower right quadrant) in TSS, and on the contrary, those regions with negative PC2 (lower right quadrant) of Chl-a are located in the positive side of PC2 (upper right quadrant) in TSS. This finding is an interesting feature and will be discussed later.

It is noted that the MODIS-derived Chl-a concentrations would be overestimated in the coastal waters due to non-algal components such as colored dissolved organic matters (CDOM) and suspended sediments (SS) since the Chl-a algorithm (OC3) for the MODIS data works well for the clear open ocean waters. The YS belongs to the marginal seas with “Case 2” optical complexities although central area of the YS is characterized as “Case 1” water during the summer months (Yoo and Park, 1998), which was also confirmed by the present study (Fig. 3b; see section 3.2 for more detail). This “Case 2” water characteristics may be due to the large volume of freshwater discharge from Yangtze and Han Rivers (Shen et al., 1998; Lee et al., 2013), and to strong tidal mixing and shallow bathymetry in coastal regions of the YS (Ahn et al., 2004). It is also due, in part, to the bifurcation of the Kuroshio Current and its complicated physical properties transporting suspended materials into the YS (Lie et al., 1998, 2001; Tseng et al., 2000; Lie and Cho, 2002; Ichikawa and Beardsley, 2002; Chu et al., 2005)

Despite the fact that TSS adds optical complexities to ocean color retrieval (Chl-a) and that both Chl-a and TSS concentrations are, in general, found to be high along the KWC, there are some spatial patterns that can distinguish Chl-a departure from TSS images in the KWC. While TSS is significantly higher in the A9 (Mokpo Bay) and A10 (Wando Coast), Chl-a is relatively lower than other KWC regions by examining seasonal Chl-a climatology patterns (Fig. 3b). In specific, this decoupling was pronounced during the plant growing season (April and May). Region A9 and A10 show low Chl-a concentration even when there are offshore (middle of the YS) blooms occur in April (Fig. 3b), and TSS climatology still reveals higher concentration during the same months in those regions (Fig. 3c).

On the contrary, regions located in the middle part of the KWC (e.g., A3-A6), Chl-a concentrations are relatively higher during April through September (see Fig. 3b), but TSS values are relatively lower compared to adjacent regions (e.g., A1, A2, A9 and A10) for the same months (Fig. 3c). The same feature was found in *in situ* measurements collected from A4–A6 regions during 2005–2007 (Fig. 4b). This indicates that despite the algorithmic limitation of “Case 1” ocean color product when applied to “Case 2” waters, the spatial distribution of MODIS-derived Chl-a in the KWC gives synoptic information about regional trends and patterns over larger areas and longer time periods, without necessarily having too much bias due to coastal TSS. However, authors should point out that it is not clear whether discrepancies between satellite-derived data and in situ measurements are due to optical algorithms in the turbid waters or due to mismatches of sampling period (monthly and quarterly) and spatial averaging. Until this question is resolved, these apparent differences will limit the quantitative usefulness of this approach to informing ecosystem managers. Continued efforts of coastal optical calibration/validation surveys are necessary in order to more accurately and quantitatively partition each water quality constituents (e.g., Chl-a, TSS, CDOM) from the optically complex coastal waters.

As previously described, the MODIS-derived TSS show strong seasonality of higher values during winter and lower values during summer. However, this seasonality pattern is not clear in the *in situ* measurements from K-MEMS (Fig. 4c). This could be attributed to the spatial heterogeneity of TSS, where high concentration of sediment may occur as patchy and point observation data may not be representative for the region. It is hard to find correlation among regions, which indicates that the processes controlling TSS could be local rather than regional. TSS is strongly affected by resuspension and physical processes, such as wind-induced winnowing, tidal currents and bottom topography, which makes it difficult to accurately estimate TSS concentration remotely from the space (Kang et al., 2009; Choi et al., 2012). In addition, increased human activities, such as coastal land cover/land use changes and coastal engineering projects, add more complexities in the coastal physical processes and dynamics of water quality indicators (Choi et al., 2012; Jung and Kim, 2005). Recently, there have been studies on diurnal features of TSS changes in the KWS, YS and East China Sea using Geostationary Ocean Color Imager (GOCI) sensor (Kim et al., 2014; Son et al., 2014) to investigate physics-induced (mostly, tides and topography) hour-to-hour variations of TSS. However, it should be noted that neither MODIS-derived TSS nor K-MEMS *in situ* measurements in this study reflect high temporal frequency (hourly time scale) signatures. Thus, satellite-derived TSS data and results presented here are more suitable for analyzing the regional and monthly climatological characteristics of suspended sediment distribution in the KWS. Son et al. (2014) investigated temporal variations in TSS concentration in the turbid coastal waters (including Gyeonggi Bay and Wando Coast), and also suggested that the satellite approaches can be applicable to synoptic studies of sediment dynamics in these areas influenced by strong tidal current.

Figure 5 reveals that almost all the PC1's from the MODIS-derived Chl-a and TSS at the study regions (except for A9) in the KWC are located on the positive side of PC1 axis, which implies that all the regions have very similar temporal structure, while there exists spatial heterogeneity in the two time series indicated by two clusters along the PC2 axis. Although having almost the same temporal structure mentioned above, it is notable that the distribution of Chl-a along the PC1 shows a more widely spread pattern than that of TSS which has a more or less narrowly aligned pattern along the PC1. In fact, biplot structure of TSS resembles that of SST (not shown in Fig. 5), which indicates that TSS concentration is more or like a quasi-conservative tracer (i.e., depending on seasonality); whereas, Chl-a shows a non-conservative property having intrinsic biological processes governing local growth and loss of phytoplankton biomass. Besides differences in the intrinsic rate, another possible explanation may include resuspension-induced TSS dynamics. Wynne et al. (2006) reported that inorganic sediment contributes up to 94% of total resuspended materials in the Texas coasts, while resuspended benthic algae is 6%. This may indirectly explain why TSS, as a quasi-conservative tracer, strongly influenced by physical processes revealed similar structure to SST in eigenvectors of covariance matrices (i.e., loadings).

Then what caused spatial heterogeneity in both Chl-a and TSS time series? Choi et al. (2003) found that relatively low primary production is found near Gyeonggi Bay (A1) and the southwestern KWC (A9 and A10), while central waters of the YS is productive during the field campaign in 1997 (February, April, August, October and December). In addition, high Chl-a concentration was found near the Taean coastal area (A3) and Cheonsu Bay (A4) where there was tidal front extended from the offshore (Choi, 1987; Seung et al., 1990; Choi et al., 1995). Similar spatial pattern was found in the monthly climatology of MODIS-derived Chl-a as previously mentioned (Fig. 3b). In general, chlorophyll dynamics in the coastal zones is influenced by temperature for growth, nutrients loadings, species composition (size fraction) of phytoplankton, light condition, and mixing/stratification. The YS and KWC have many complexities with respect to land-sea hydrology, tidal influences, seasonal bottom cold water mass and current features associated with Kuroshio bifurcations (Lie, 1986; Choi, 1987; Seung et al., 1990; Choi et al., 1995).

Tidal currents-induced resuspension and transport are dominating processes in TSS dynamics (Lee et al., 2013; Son et al., 2014). Diurnal (hour-to-hour) variations in TSS assessed with GOCI clearly demonstrated that TSS dynamics in Gyeonggi Bay (near A1 and A2) and Wando Coast (near A9 and A10) is strongly influenced by tidal currents, e.g., tidal asymmetry effect in stratification (see the discussion in Son et al., 2014), while other middle regions of the KWC (e.g., Taean Coast, Cheonsu Bay, Saemangeum Dike) do not seem to have as strong tidal effects as Gyeonggi Bay and Wando Coast have because tidal influence and topographical settings are different.

Although minor discrepancies exist between the two PC1's from MODIS-derived Chl-a and TSS, both time series are found to have strong cross spectral power at the frequency of 1 year (Fig. 6b), which implies that there is a strong seasonality in both properties. Interestingly, the phase between the two is 6 months apart (Fig. 6a and 6d). This strong negative cross correlation is presumed to be largely due to strong seasonal variabilities that YS environmental factors have. Son et al. (2014) reported that the sediment dynamics of the YS and East China Sea is characterized with strong seasonality, showing highest in winter and lowest in summer months. This seasonal pattern is related to many factors that also affect SST in the region, such as monsoon, advection, vertical mixing and bottom topography (Furey and Bower, 2005, Xie et al., 2002). In specific, basin scale atmospheric pressure system (i.e., monsoon) and the bathymetry effects play a critical role in creating these seasonal trends because these two factors will change features of wind-induced mixing (waves and surface currents), resuspension, and thus, TSS dynamics, consequently. Likewise, overall chlorophyll dynamics in the coastal zones is strongly influenced by optimal temperature, nutrients and light availability for photosynthesis. Although complicated oceanographic conditions exist, phytoplankton growth generally occurs during spring, summer and fall season in the YS and KWC regions (Choi, 1987; Lie, 1986; Seung et al., 1990; Choi et al., 1995). Therefore, authors speculate that 6-month phase-lag between MODIS-derived Chl-a and TSS is largely due to strong inversed seasonality caused by different sets of drivers both properties have. It is not clear whether there is a certain connection in ecosystem dynamics between the two properties.

So far, there have been few studies between year-to-year variations of SST in the YS with basin-scale changes, such as linking to ENSO (Park and Oh, 2000; Wu et al., 2005), although some researchers focused on long-term warming trends of SST related to atmospheric patterns (Yeh and Kim, 2010; Park et al., 2015). It has been believed that there is a rather distinct teleconnection between changes in winter SST in the YS and ENSO. The present study found that there was a significant positive cross-correlation between the PC1 of SST measurements from K-MEMS and NIÑO3.4 index (not shown). Interestingly, the teleconnection of the PC1 from the Chl-a time series with NIÑO3.4 differed from the above SST case. Figure 7 presents PC1 (EOF mode 1) from chlorophyll time series overlaid by NIÑO3.4 index that is a representative climate index for ENSO. Positive index represents warmer than normal (El Niño mode) and negative index represents colder than normal (La Niña mode), respectively. Although not significant, it is notable that there is slight negative cross-correlation between the PC1 coefficients and NIÑO3.4 (Fig. 7d), which was also found in K-MEMS measurements with different time-lags (not shown). Authors speculate that this negative relationship may be related to ENSO-induced changes in terrestrial settings (e.g., quality and quantity of riverine discharges), changes in far-field physical processes (e.g., mixing patterns in the offshore of the YS and Kuroshio bifurcations, possibly), and/or changes in phytoplankton physiological responses or community structures. It certainly requires further investigation in the future.

There are many eutrophication assessment frameworks: Marine Strategy Framework Directive in European Commission; Australian National Water Quality Management Strategy; Oslo Paris (OSPAR) Commission Common Procedure; Water Framework Directive (WFD) in European Union; French Research Institute for Exploration of the Sea (IFREMER) method; Helsinki Commission (HELCOM) Eutrophication Assessment Tool; USA the National Coastal Assessment and National Aquatic Resource Assessment (Park, et al., 2010; Devlin et al., 2011; Ferreira et al., 2010; Dekker and Hestir, 2012).

However, few management decisions are made based on satellite-derived products (Schaeffer et al., 2013).

Good ecosystem-based coastal managements always require comprehensive and quality-assured data and this requirement cannot be fulfilled by only spatio-temporally limited, cost and labor intensive *in situ* monitoring data (Bierman et al., 2011). Remote sensing can provide information embedding various spatio-temporal scales and complex dynamics of coastal processes (Schaeffer et al., 2013; Kratzer et al., 2014). For example, remote-sensing technique successfully monitored toxic cyanobacterial blooms in the Baltic Sea (Kahru et al., 2007; Kononen and Leppanen, 1997), Great Lakes and the eastern USA (Lunetta et al., 2015). Although this kind of success stories encourages management level to incorporate remotely sensing tool as a component of integrated coastal zone management, it should be kept in mind that satellite technique cannot solve all the problems managers and policy makers may have, and that there are technical and logistic limitations to be resolved (e.g,, product accuracy, data continuity, programmatic support and cost issues discussed in Schaeffer et al., 2013).

In conclusion, MODIS-derived water quality indicators from the Korean west coast waters indicate that: 1) there is a strong seasonality in decomposed principal components of SST, Chl-a and TSS time series with spatial heterogeneity between the north-south group (Gyeonggi Bay, Mokpo Bay, Wando Coast) and mid-coast group (Cheonsu Bay, Boryeong Coast, Saemangeum Dike); 2) there is a six-month phase-lag between Chl-a and TSS due to strongly inversed seasonality both properties have, which can be explained by different dynamics between the two. Chl-a in the coastal zones is influenced by temperature for growth, while TSS is strongly influenced by tidal forcings and bottom topography; 3) Chl-a may possibly be tele-connected with ENSO events negatively. Remote-sensing technique can provide quantitative and supplemental information and serve as an important decision supporting tool in coastal management.

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**Figure captions**

Figure 1. Map of the west coast of Korea (West Sea, eastern part of the Yellow Sea), showing 10 regions (colored boxes) where satellite data were acquired; and 105 monitoring stations where water quality indicators were measured *in situ* (red dots). These ten regions are delineated by bays and river discharges. Names of bays and coasts representing each area are as follows: Gyeonggi Bay (A1); Asan Bay (A2); Taean Coast (A3); Cheonsu Bay (A4); Boryeong Coast (A5); Seocheon Coast (A6); Saemangeum Dike (A7); Gochang Coast (A8); Mokpo Bay (A9); and Wando Coast (A10). Water quality indicators were seasonally monitored along the west coast of Korea by the Korea Marine Environmental Monitoring System (K-MEMS) since 1997 to the present (a total of 105 stations).

Figure 2. MODIS-derived long-term climatology images in the west coast of Korea (July 2002-Dec 2014). (a) sea surface temperature (SST), (b) chlorophyll-a (Chl-a), and (c) total suspended solids (TSS) of surface waters.

Figure 3. MODIS-derived monthly climatological images in the west coast of Korea (12-year mean for each month, July 2002-Dec 2014). (a) sea surface temperature (SST), (b) chlorophyll-a (Chl-a), and (c) total suspended solids (TSS) of surface waters.

Figure 4. eleven-year time series data sets of (a) sea surface temperature (SST), (b) chlorophyll-a (Chl-a), and (c) total suspended solids (TSS) in 10 regions (A1-A10). Solid red lines with square symbols represent quarterly *in situ* measurements from K-MEMS stations, and solid blue lines represent MODIS-derived monthly data.

Figure 5. Biplots of MODIS-derived (a) chlorophyll-a (Chl-a) and (b) total suspended solids (TSS) from 10 regions. Circles represent two groups of regions revealing spatial heterogeneity along the principal component (PC) 2 axis. Variance explained by 10 PCs are presented for (c) Chl-a and (d) TSS. PC1 and 2 represent temporal and spatial decomposition of the original time series data. The strongest explanation power that PC 1 has is 47.3% (Chl-a) and 74.6% (TSS).

Figure 6. Time series analysis of chlorophyll-a (Chl-a) and total suspended solids (TSS) derived monthly from MODIS (July 2002-Dec 2014). (a) Principal component 1 (EOF mode 1) of Chl-a time

series overlaid by that of TSS time series. (b) Cross spectral power, (c) coherence and (d) cross correlation coefficients for time lags are presented. Horizontal dashed lines in grey and black color in (c) and (d) represent upper (95%) and lower (90%) limits of confidence interval, respectively. The vertical dashed line in (d) represents the point where the two time series have no phase-shift (zero phase-shift).

Figure 7. Time series analysis of monthly chlorophyll-a (Chl-a) derived from MODIS (July 2002-Dec 2014). (a) Principal component 1 (EOF mode 1) of Chl-a time series overlaid by NIÑO3.4 index. Positive index represents warm years when El Niño mode happens and negative index represents cold years when La Niña mode happens. (b) Cross spectral power, (c) coherence and (d) cross correlation coefficients for time lags are presented. Horizontal dashed lines in grey and black color in (c) and (d) represent upper (95%) and lower (90%) limits of confidence interval, respectively. The vertical dashed line in (d) represents the point where the two time series have no phase-shift (zero phase-shift).