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MODIS ocean color product downscaling via spatio-temporal fusion and regression: The case of chlorophyll-a in coastal waters

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ABSTRACT

Detailed and accurate information on the spatial variation of chlorophyll-a concentration in coastal waters is a critical component of ocean ecology and environmental research. The daily MODIS chlorophyll-a products provided by NASA, with 1 km spatial resolution, are suitable for monitoring this variation globally, but these products are too coarse to apply in practice to obtain detailed information over coastal waters. Early studies have shown that spatiotemporal data fusion techniques can be used to predict higher spatial resolution land-cover data based on time-series information in MODIS and the detailed texture from Landsat. However, this technology hasn't been tested to determine whether it can be used to predict higher spatial-resolution data in coastal waters with rapid water movement. This study aims to answer this question by providing a method to downscale the MODIS chlorophyll-a products from 1 km spatial resolution to 30 m. The spatiotemporal data fusion model U-STFM and the regression model NASA OC2M-HI were used to combine the texture and chlorophyll-a information from Landsat and MODIS. An area with rapid water movement in Bohai Bay of the Bohai Sea, northeast China, was selected for this study. Twelve matched images from MODIS in Aqua platform and Landsat 8, taken over a period of five years (2013–2017), were used to better predict detailed remote-sensing reflectance (Rrs) on the targeted days. Landsat 8 Rrs was used as ground-truth data to assess the output. The results on Mar 10th, 2016, show: 1) The downscaled results (30 m) from the U-STFM model indicate a more stable prediction of Rrs with RMSE of 0.00177 and 0.00202 and R-squared of 0.868 and 0.881 for the blue and green bands, respectively. Results from STARFM and ESTARFM fusion models are also compared in this study. 2) High correlation between log10(U-STFM Blue/ U-STFM Green) and log10(MODIS Chl) captured by OC2M-HI regression model at 1 km scale with R-squared up to 0.85 and RMSE up to 0.742 mg/m^3. This correlation was further used to predict the final chlorophyll-a concentration prediction at 30 m scale on Mar 10th, 2016; 3) The Landsat 8 chlorophyll-a product was used as reference data to evaluate the final chlorophyll-a concentration prediction (30 m) and the original MODIS chlorophyll-a product. The result shows the final prediction (30 m) maintains the accuracy of MODIS chlorophyll-a product and highly improved the local texture details near coastal waters. Predictions on nine other targeted dates with similar conclusions were also evaluated in this paper. The results in this study suggest that low spatial-resolution (1 km) daily MODIS chlorophyll-a products can be downscaled to higher resolution (30 m) products based on the U-STFM image fusion model and NASA's OC2M-HI regression model to better understand the dynamic patterns of chlorophyll-a concentration in coastal waters.

1. Introduction

Ocean color is an essential factor for understanding the dynamic ocean biosphere process (Esaias et al., 1998). Based on the high revisiting frequency (twice a day) of the Tarra and Aqua platforms, MODIS ocean color products from NASA have been widely used in the monitoring of ocean dynamics and global environment changes in the past few decades (Dasgupta et al., 2009; Esaias et al., 1998; McClain,

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2009). Water quality in coastal waters, which reflects the interactions between humans and the local environment, is a common area of concern in ocean science (Cherukuru et al., 2016). However, the detailed information in coastal waters is difficult to capture using the NASA MODIS ocean-color products, considering the low spatial resolution of this data (1 km). Therefore, obtaining both high spatial and temporal resolution data in these areas is an urgent requirement for understanding the biological processes in coastal environments (Esaias et al., 1998; McClain, 2009).

In the last decade, efforts have been made to focus on how to improve the spatial resolution of coarse image observations in both computer vision and remote-sensing fields (Yang et al., 2010; Yue et al., 2016). Two major groups of techniques were developed to answer this question: image super-resolution techniques and spatiotemporal data fusion.

In the super-resolution field, the basic assumption is that the missing details in a low spatial-resolution image can be either reconstructed or learned from other high spatial-resolution images if these images follow the same resampling process as was used to create the low spatial-resolution image (Fernandez-Beltran et al., 2016; Zurita-Milla et al., 2008). In these methods, the key step is to accurately predict the point spread function (PSF), which represents the mixture process that forms the low-resolution pixels (Yue et al., 2016). The PSF can be created based on image reconstruction (RE) technology, such as iterative back projection (IBP) and PSF deconvolution. These techniques extract certain physical properties and features to provide more detailed information about low spatial-resolution images and aggregate this information with regular interpolated results to obtain the final super-resolved image (Fisher and Mustard, 2004; Miskin and MacKay, 2000; Takeda et al., 2007). The point spread function can also be created based on image learning technologies when a large number of image samples are available, such as in convolutional neural network (CNN)(Dong et al., 2016), sparse coding (Yang et al., 2010), Bayesian networks (Lu and Qin, 2014), kernel-based methods (Takeda et al., 2007), and SVM-based methods (H. Zhang and Huang, 2013). However, in practice, the actual mixing process of low-resolution remote-sensing images could be too complex to be captured by one universal PSF based on limited samples. Furthermore, the accuracy of these methods decreases rapidly when the scale ratio gets larger. The common downscaling ratio of most super-resolution algorithms is 2–4. Conversely, the scale ratio between MODIS and Landsat data is 1 km/30 m = 33.3. With this huge difference of scales, these methods have limited application in downscaling MODIS data from 1 km to 30 m.

To avoid building the PSF and predicting image details, spatiotemporal data fusion techniques get higher spatial resolution texture details by merging fine images to coarse images, following certain rules. When there is no fine spatial resolution data available, fine time-series data is used as ancillary data to provide the details at the same location (Chen et al., 2015). These spatiotemporal data fusion techniques are based on two assumptions: the scale invariance of temporal information and the temporal constancy of spatial information (Zhang et al., 2015). Compared to super-resolution methods, time-series image fusion technology does not predict high-resolution details directly from the coarse data. Instead, it combines the details revealed in time-series high spatial-resolution images at the same location. Many applications have been established based on these techniques, such as crop progress at field scales (Gao et al., 2017), NDVI time series (Zhang et al., 2016), spatial and temporal surface reflectance dynamics (Emelyanova et al., 2013), gross primary productivity (Singh, 2011), vegetation seasonal dynamics (Zurita-Milla et al., 2009), forest disturbance (Hilker et al., 2009), and seasonal wetlands monitoring (Mizuochi et al., 2017). To the best of our knowledge, these spatiotemporal data fusion techniques haven't been tested on ocean color products for data downscaling.

The Unmixing-based Spatial-Temporal Reflectance Fusion Model (U-STFM) introduced by Huang and Zhang was used as the spatiotemporal data fusion technique in this study because it was announced to be more adaptable to land-cover changes (Huang and Zhang, 2014). The U-STFM combines the change ratio in time series with the linear decomposition model of mixed pixels to provide a new processing structure for time-series image fusion on rapidly changing landscapes. This method has been well tested in land-cover change applications, such as MODIS land surface reflectance downscaling, and has demonstrated its effectiveness (Huang and Zhang, 2014). The question is how to use this model to face the downscaling problem in ocean color products.

When applying U-STFM to downscale the MODIS ocean color chlorophyll-a concentration products, two issues need to be addressed. Firstly, the U-STFM model requires the consistency of the change ratio in both fine and coarse time-series data. However, this consistency of the change ratio is destroyed by involving different models with bias and variance during atmosphere correction and chlorophyll-a retrieval processing in MODIS and Landsat ocean surface chlorophyll-a concentration products (e.g., instrument calibration, atmospheric correction, inversion algorithms) (Pahlevan et al., 2016). Secondly, in U-STFM, it is necessary to decrease the size of the segmentation regions to obtain a more accurate changing ratio for each segmentation region in order to provide more detailed information in the final output. However, smaller regions may cause inconsistent solutions in the linear unmixing equations, which will lead to data gaps or unreasonable predictions in the final output. More inconsistent solutions appear as "the hard boundaries" when applying U-STFM to detect more fragmented changes, such as the changes of chlorophyll-a concentration in coastal waters.

Therefore, in this study, we focus on these two main issues to extend the applications of U-STFM from inland areas to coastal waters for downscaling the spatial resolution of MODIS daily ocean surface chlorophyll-a concentration products from 1 km to 30 m. The Port of Tangshan Caofeidian in China, located in northeast Bohai Bay, was used as the case study area. Landsat 8 ground-truth remote-sensing reflectance (Rrs) and chlorophyll-a concentration products were used as reference data to assess the quality of final downscaled chlorophyll-a concentration products. In this study, the Rrs prediction results from the commonly used Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao et al., 2006) and Enhanced STARFM (ESTARFM) (Zhu et al., 2010) were also compared to the result from the U-STFM model. The major contributions of this study are as follows:

- Provides a way to extend the application of the U-STFM model from inland surface reflectance data to ocean color products.
- Predicts higher spatial resolution daily ocean surface chlorophyll-a concentration product in coastal water. The accuracy of this product remains the same as the original MODIS chlorophyll-a products but with more details in coastal waters.
- The method provided in this study can be further applied to other ocean color products, such as sea surface temperature, Kd490. This data can be further applied to build physical simulation models to better understand the dynamic changes in coastal waters.

2. Methodology

2.1. Basic idea

The U-STFM model requires the same change ratio for pixels or regions on both fine and coarse spatial resolution time-series data. Since the consistency of the change ratio in MODIS and Landsat chlorophyll-a products can be destroyed by the different chlorophyll-a retrieval models (Pahlevan et al., 2016), it is difficult, if not impossible, to directly apply U-STFM on MODIS and Landsat chlorophyll-a products. However, compared to the processed products, the consistency of the change ratio can be maintained in the initial MODIS and Landsat Rrs with similar atmospheric correction processes (Pahlevan et al., 2017). The purpose of this research was to first predict the Rrs on the targeted