Spatiotemporal Variation of Sea Surface Temperature Based on Landsat-8 in Tokyo Bay

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1 Introduction

1.1 Background

1.1.1 Importance of Measuring Sea Surface Temperature

Sea surface temperature (SST) is a fundamental physical variable for understanding, quantifying and predicting complex interactions between the ocean and the atmosphere, not only indicates the global climate change but also revealing productivity of harvesting closely related to anthropogenic activities. It has been proved that SST plays an important role in responses of the seagrass meadows. But recently a down-fall in seaweed production and seagrass meadows have been experienced in some areas for certain species due to warming oceans [1]. Many factors have been proposed that could lead to an increase in seawater temperature around coastal areas, including thermal discharge from power plants.

1.1.2 Thermal Discharge from Power Plants

In thermal or nuclear power plants, electricity is generated by rotating turbines with high-temperature steam. After use, the steam is sent to a condenser where it is cooled back to water and used again in the boiler or nuclear reactor (steam generator). Because Japanese power plants are located near the coast, the condenser is seawater-cooled, and the seawater used to cool the steam in the condenser is discharged directly into the ocean as warm wastewater. Most previous studies have shown that the thermal discharge can increase seawater temperature, which directly affects the environmental temperature of marine organisms [2]. The thermal discharge on aquatic ecosystems has become an important issue in the field of marine and environment protection.

1.1.3 Application of Remote Sensing to SST Analysis

The increasing amount of power produced by fossil fuel and nuclear power plants makes it important to monitor the thermal pollution in coastal waters. Much of research on this problem has focused on the assessment of the impact to marine biological communities. It is fundamental to detect the intensity of heated effluent discharge and its spatial and temporal properties [3].

The conventional method for investigation of this kind of thermal pollution is to measure the water temperature from point to point, a major expense in time and money. With in-situ measurements it is hard to get accurate distributions of the thermal discharge because of tides and advection.

In recent years, satellite-based sensors like Landsat and Sentinel have been successfully used to estimate and visualize the distribution of coastal sea surface temperature. Since the launch of Landsat 8, high-quality sea surface observation data have been acquired. But the corresponding sea surface temperature products have not been seen, sea surface temperature images still need to be obtained based on retrieval algorithms.

1.2 Objectives

A few studies have proposed land surface temperature (LST) retrieval algorithms for the Landsat series. While most algorithms are simple to implement, they require users to provide the necessary input data and calibration coefficients, which are generally not readily available. Since the data are only accessible through the web application, common methods still require users to download large amounts of data if they wish to perform time-series analysis. Google Earth Engine (GEE) is an online platform created to allow remote sensing users to easily perform big data analysis without increasing the demand for local computing resources.

As mentioned by Sofia L. Ermida et al [5], a relatively new approach has been developed to derive Landsat LST based on GEE. Unfortunately, the code cannot be directly utilized for SST retrieval. Furthermore, modifications are still required under some circumstances for SST mapping efficiently. Hence, this study aims to make clear the spatiotemporal variation of SST based on satellite data. To be more specific, first, modify and develop the code to make it more applicable in efficient SST mapping. Second, visualize and identify the SST distribution patterns in the study site especially in coastal zones that are easily affected by thermal power plants through GEE.

2 Materials and Methods

2.1 Study Site Description

Tokyo Bay is located in the southern Kantō region of Japan. Most of the thermal power plants owned by Tokyo Electric Power Company (TEPCO) are located along the coast of Tokyo Bay (Fig. 2.1).

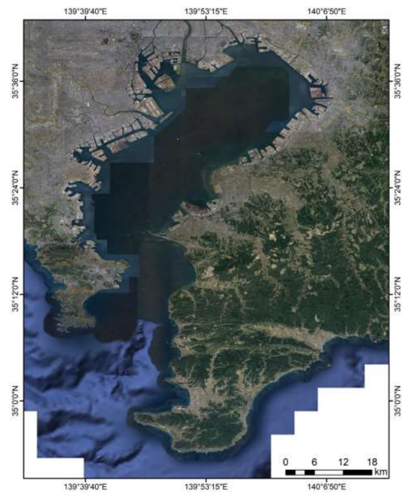

Fig. 2.1 Tokyo Bay

A sandy tidal flat spreading on the northeast side of Cape Futtsu, a cape located east of Tokyo Bay (Fig. 2.2). There are seaweed beds of eelgrass, and the eastern part is a tidal flat. Futtsu tidal flat has the largest remaining eelgrass bed in Tokyo Bay.

Fig. 2.2 Futtsu Tidal Flat

Wajiro Tidal Flat is a tidal flat of about 80 hectares in the area located at the northeastern end of Hakata Bay (Fig. 2.3).

Fig. 2.3 Wajiro Tidal Flat

2.2 Data and Algorithms

2.2.1 Landsat 8 Data

The Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) makes it possible to obtain high-resolution SST images of coastal regions. The satellite has a 16-day repeat cycle and thermal band 10 and 11 are collected at 100 meters [4].

2.2.2 Retrieval Algorithm

The algorithm used in this study was developed by CM-SAF which has been proved to be suitable for GEE platform [5]. It was used for LST retrieval initially. LST is computed with the Statistical Mono Window algorithm (SMW), while the approach is based on an empirical relationship between TOA brightness temperatures in a single TIR channel and LST and utilizes simple linear regression. The model consists of a linearization of the radiative transfer equation that maintains an explicit dependence on surface emissivity:

$$LST = A_i \frac{T_b}{\varepsilon} + B_i \frac{1}{\varepsilon} + C_i \tag{1}$$

Surface Emissivity:

$$FVC = \left(\frac{NDVI - NDVI_{bare}}{NDVI_{veg} - NDVI_{bare}} \right)^2 \tag{2}$$

$$\varepsilon_b = FVC\varepsilon_b + (1 - FVC)\varepsilon_{b,bare} \tag{3}$$

where T_b is the TOA brightness temperature in the TIR channel, and ε is the surface emissivity for the same channel. The algorithm coefficients Ai, Bi and Ci are determined from linear regressions of radiative transfer simulations performed for 10 classes of TCWV (I = 1,…,10), ranging from 0 to 6 cm in steps of 0.6 cm, with values of TCWV above 6 cm being assigned to the last class.

2.2.3 Monitoring Station Data

The quality of the SST data retrieved with the algorithm described above is evaluated by comparing with monitoring station data. In this study, hourly monitoring data is obtained from official websites by Tokyo Bay Water Quality Continuous Observation [6].

3 Results and Discussion

3.1 Spatio-Temporal Variation

Eight years (2013-2020) original Landsat 8 data has been obtained and calculated for SST retrieval based on the GEE platform, automatically in this study. Since Landsat satellites image the entire Earth every 16 days, as well as the relatively bad cloud cover condition above Tokyo Bay, images that can be utilized for further discussion are almost less than 8 each year.

Based on images of average SST distribution in four seasons in Tokyo Bay, it can be concluded that the spatial pattern of SST varies in four seasons, which was probably affected by air temperature, precipitation, wind speed, and water depth. The usefulness of Landsat 8 for the analysis of SST changes over small-scale areas has been demonstrated in this study since the thermal plume discharged by thermal power plants can be clearly shown on the SST spatial distribution images and spatial gradient images which has a non-negligible impact on the water environment around the power plants especially in autumn and winter. The SST near the coast is higher totally compared with offshore SST.

3.2 Discussion on Seagrass Meadows

The SST distribution maps are consistent with the official report results about Futtsu Tidal Flat and Wajiro Tidal Flat. It indicates that Landsat 8 is applicable based on efficient temperature monitoring to seaweed and seagrass habitats along coastal areas since high-resolution imagery is most in need. Especially, Landsat 8 can be utilized for predicting and alerting possible future conditions of seagrass and seaweed beds in those areas without in-situ monitoring buoys.

4 Conclusions

This study analyses the spatial-temporal variation in sea surface temperature from Landsat 8 OLI which has a higher resolution compared with other commonly used satellites. The main tool for processing satellite data and completing statistical calculation is Google Earth Engine which is an efficient online platform especially when it comes to processing several years of data.

Totally, the spatial pattern of SST varies in four seasons, which is mainly affected by topography and water exchange. In the coastal areas, the spatial pattern of SST in different seasons also indicates the influence of thermal power plants and water depth on SST. With two examples of Tokyo Bay and Hakata Bay, the SST distribution corresponds to seagrass beds' growth or disappearance condition. It has been proved that Landsat 8 using on GEE platform is applicable based efficient temperature monitoring and processing to seaweed and seagrass habitats management.

Reference

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