**Cyberspace**: Jurnal Pendidikan Teknologi informasi
Volume 8, Nomor 2, Oktober 2024, hal. 54 - 60
ISSN 2598-2079 (print) | ISSN 2597-9671 (online)

# FUSING SATELLITE DATA TO MONITOR SEA LEVEL CHANGES: A DEM-BASED NEAREST NEIGHBOR APPROACH

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**Abstract**

High spatial and temporal resolution satellite imagery is essential for monitoring rapid environmental changes at finer scales. However, no single satellite currently provides images with both high spatial and temporal resolution. To overcome this limitation, spatiotemporal image fusion algorithms have been developed to generate images with improved spatial and temporal detail. Water level monitoring is also crucial for managing natural hazards like floods and tsunamis, but remote sensing satellites face challenges in continuous monitoring due to either low spatial or temporal resolution. For instance, while Landsat 8, with a spatial resolution of 30 meters, has been used for water level detection, it cannot capture fast-changing events because of its low temporal resolution. Conversely, the Advanced Himawari Imager (AHI) 8 offers observations every 10 minutes but has a coarse spatial resolution, limiting its ability to map sea level changes accurately. This study focuses on integrating Landsat and AHI imagery to monitor local and dynamic sea level changes. The process involves calibrating images from the study area to surface reflectance and co-registering them. The Normalized Difference Water Index (NDWI) is calculated from both Landsat and Himawari-8 images, serving as input for image fusion. In the previous study, the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) is used for image fusion. In this study we use the application of Spatial Temporal Adaptive Algorithm for Mapping Reflectance Change (STAARCH) for the image fusion step. Since traditional methods are influenced by land cover changes, this study proposes a method called DEM-based Nearest Neighbor to select appropriate land cover maps for image fusion. Evaluation results demonstrate that this approach can produce accurate water coverage maps with both high spatial and temporal resolution.
**Keywords:** *image fusion, sea level change, water index, nearest neighbor*

## 1. Introduction

Remote sensing has revolutionized environmental monitoring by providing valuable data for tracking large-scale phenomena like sea level variations, coastal erosion, and natural disasters. However, one of the significant limitations of individual sensors is the trade-off between spatial and temporal resolution, which makes it difficult to obtain high-quality, frequently updated imagery. Image fusion techniques have emerged as a solution to this challenge by integrating data from multiple sensors to produce images with enhanced spatial and temporal characteristics [1]. This approach is particularly important for applications that require both high spatial detail and frequent updates, such as sea level monitoring, disaster preparedness, and climate change analysis [2].

Image fusion refers to the process of merging data from multiple sensors, leveraging their respective strengths. For instance, satellites like Landsat provide high spatial resolution (30 meters) but have lower temporal resolution (revisit time of 16 days), while geostationary satellites like Himawari-8 provide high temporal resolution (10-minute intervals) but at the cost of spatial detail. Through image fusion, these datasets can be combined to create an output that offers both frequent updates and fine spatial resolution, making it possible to monitor dynamic environmental changes with greater accuracy [3].

One advanced method that relates closely to image fusion for monitoring dynamic surface changes is the Spatial Temporal Adaptive Algorithm for Mapping Reflectance Change (STAARCH). STAARCH is an algorithm specifically designed to detect land cover changes using satellite imagery. It is particularly useful for identifying reflectance changes over time, enabling the tracking of phenomena such as vegetation shifts, urban expansion, and water surface changes due to rising sea levels. STAARCH leverages the temporal information from high-frequency satellite observations and spatial detail from high-resolution sensors to detect changes with greater precision [4].

For instance, STAARCH can use frequent, low-resolution data from MODIS or Himawari-8 to monitor ongoing changes in sea levels or coastal environments, while simultaneously incorporating high-resolution data from Landsat or Sentinel-2 to accurately map the location and scale of these changes. This combination allows for detecting both subtle and significant shifts in reflectance, enabling more accurate identification of environmental changes such as flooding, deforestation, or urban sprawl [5].

Therefore, the primary goal of this research is to explore the feasibility of using spatial and temporal image fusion techniques for the efficient monitoring the sea level changes by using the proposed Digital Elevation Model (DEM)-based Nearest Neighbor (DNN) method. This goal will be accomplished through four initial steps, as detailed in the following section: first, generating 30-meter NDWI images of the coastal area; second, simulating the NDWI images as the reference, third, blending the images from Himawari and Landsat; and fourth, evaluating the water coverage. A detailed explanation of each of these steps will be provided in the next section.

## 2. Research Method

This study examines the practicality of applying spatial and temporal image fusion techniques for efficient sea level monitoring, utilizing the proposed DEM-based Nearest Neighbor (DNN) method. To access more reference water index images as the drawback of previous study [6], in this study, we simulate more water index images of Landsat so we can examine the image fusion with more reference images. Fig. 1 shows the methodology of this study.

It started with preparing the Himawari NDWI images as the reference images. All the reference images are listed on Table I. Then to simulate the Landsat NDWI images, we need to have the water height for each reference image and the existing mNDWI images of Landsat. This water height is obtained from Tide Model (NAO.99b). We proposed a method called DEM-based Nearest Neighbor to simulate Landsat NDWI images. So, in this study we also use the DEM of the study area, the Hsianshang Wetland. After having the simulated images, we can fuse the Himawari and Landsat Images. Then as the lst step in this study, we evaluate the image fusion result by calculating the accuracy assessment metrics, such as Commission and Omission Errors, Overall Accuracy, and the Kappa Coefficient.

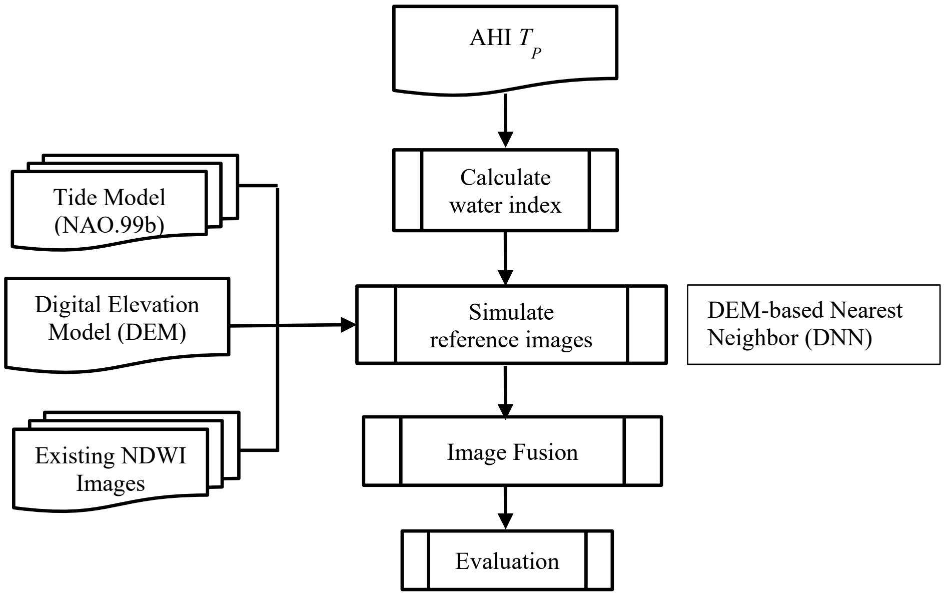


Figure 1. The methodology of the study

Table I shows the dataset that used in this study which are all the images of both Himawari-8 and Landsat OLI along with the corresponding water height. Since we have limited reference of NDWI images, we simulate the NDWI images using the existing NDWI images. The next section will give the further explanation of each step in this study.

TABLE 1. THE DATASET USED IN THE STUDY

| No. | Date | Time | NDWI Image | | Water Height(m) |
|---|---|---|---|---|---|
| | | | Himawari-8 | Landsat OLI | |
| 1 | 11/10/2017 | 10:30 a.m. | v | v | -1.595 |
| 2 | 2/4/2017 | 10:30 a.m. | v | v | -1.15 |
| 3 | 13/2/2017 | 10:30 a.m. | v | v | 0.516 |
| 4 | 26/01/2016 | 10:30 a.m. | v | v | 0.525 |
| 5 | 14/12/2017 | 10:30 a.m. | v | v | 0.748 |

The specific bands used in this study for mNDWI calculations are the Green band (0.51–0.59 μm) and band 5 or SWIR (2.11–2.29 μm). The research focuses on Hsianshang Wetland of Taiwan. This study aims to propose DEM-based Nearest Neighbor to combine satellite data from different sensors, specifically the Advanced Himawari Imager and Landsat 8. The blending process involves aligning and calibrating all the images from Hsianshang Wetland to surface reflectance using affine transformation.

After acquiring images from both Himawari and Landsat satellites, specific light bands known as Green (G) and Shortwave Infrared (SWIR) bands are applied, as demonstrated in formula (1). These bands are effective for identifying water bodies due to their unique spectral properties. The Normalized Difference Water Index (NDWI) is then calculated to quantify water presence using the data from these bands. The NDWI compares the light reflectance in the Green and NIR bands.

Once the NDWI values are generated, a threshold value of 0.4 is used to distinguish water from non-water areas. If the NDWI value exceeds 0.4, the area is classified as containing water, while values below 0.4 indicate non-water regions. This method is valuable for tracking changes in water bodies, analyzing water quality, and managing water resources. By combining satellite imagery with advanced image processing techniques, researchers and decision-makers can gain vital insights into the behavior of water bodies, helping them make informed decisions regarding water management and conservation efforts.

$$NDWI = \frac{Green\ - NIR}{Green + NIR} \tag{1}$$

The second part of this study is simulating the NDWI by proposing DEM-based Nearest Neighbor (DNN) approach. This approach is using the DEM value to be compared to the water height of each reference image. We have three terms in this approach as mention in Fig. 2. If the DEM is larger than the predicted water height and smaller than the high water height, it will defined as non-water pixel. Vice-versa, if the DEM is larger than low water height and smaller than the predicted water height, it will choose the water pixel for the simulated image. Then if the DEM is in between the high water height and low water height, it will choose the pixel value that close to the predicted water height.

*WHH: High Water Height*
*WHP: Predicted Water Height*
*WHL: Low Water Height*

```
if the DEM >= WHH or <=WHL
    choose the pixel closest to the WHP
  else DEM > WHP and < WHH
       choose LAND pixel
  else DEM > WHL and <WHP
       choose WATER pixel
```

Figure 2. The algorithm of DNN

The third phase of the blending process focuses on image fusion, where the STAARCH model is employed to predict data with high temporal and spatial resolution. STAARCH is a robust algorithm in remote sensing, designed to integrate satellite images obtained from different sensors and times. The model requires specific input data, including images from both the Himawari and Landsat satellites, along with a simulated image produced by a Deep Neural Network (DNN). Additionally, the Himawari image captured at the forecasted time and the classification map from the reference time are used. These datasets are all expressed as water index values, providing numerical information about water presence or characteristics in the study area. Following the blending process, in the evaluation phase of the study, common accuracy metrics such as the Kappa Coefficient, Commission Error, Omission Error, and Overall Accuracy are calculated to assess performance.

## 3. Results and Discussion

We assessed the viability of merging satellite images by calculating metrics such as the Kappa Coefficient, Commission Error, Omission Error, and Overall Accuracy. The aim was to confirm that the combined data accurately reflects the spatial features of the study area. For evaluation purposes, we categorized the analysis into two cases: Low Water Height and Middle Water Height.

To verify the outcomes produced by the STAARCH model, a real Landsat image was used. Additionally, we aimed to evaluate whether the reference image generated by the DNN could accurately represent the water index of the simulated image, particularly in the Low Water Height case, as depicted in Fig. 3.

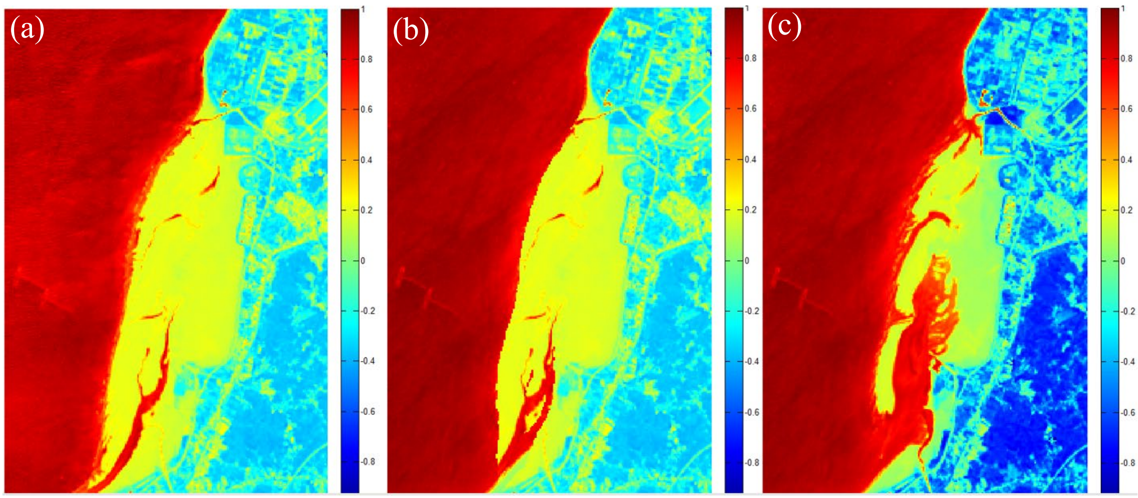


Figure 3. Low Water Height case (a) NDWI Image on 11/10/2017 (b) Simulated NDWI Reference time (c) NDWI Image on 13/02/2017

An evaluation map was generated by overlaying the predicted water map with the water map derived from the Landsat image on a pixel-by-pixel comparison, as shown in Fig. 4 of the study. This evaluation map helped highlight areas where water was misclassified, revealing discrepancies between the predicted and reference water maps. These misclassifications primarily resulted in underestimating the water area, which led to a higher occurrence of omission errors in the predicted water map. Several common accuracy metrics, such as commission and omission errors, overall accuracy, and the Kappa coefficient, were computed from the evaluation map presented in Fig. 4 and are summarized in Table II of the study.

These indices provide quantitative measures to assess the accuracy and reliability of the predicted water map generated by STAARCH which reference images simulated by DNN approach. The values obtained for the accuracy evaluation indices as shown in Table 4, particularly the Kappa coefficient and overall accuracy, offer insights into the level of agreement between the predicted water map and the reference map derived from the actual Landsat image. High values of Kappa and overall accuracy indicate a strong consistency between the predicted and reference maps, suggesting that the predicted image generated by STAARCH closely aligns with the actual water distribution captured by Landsat imagery.

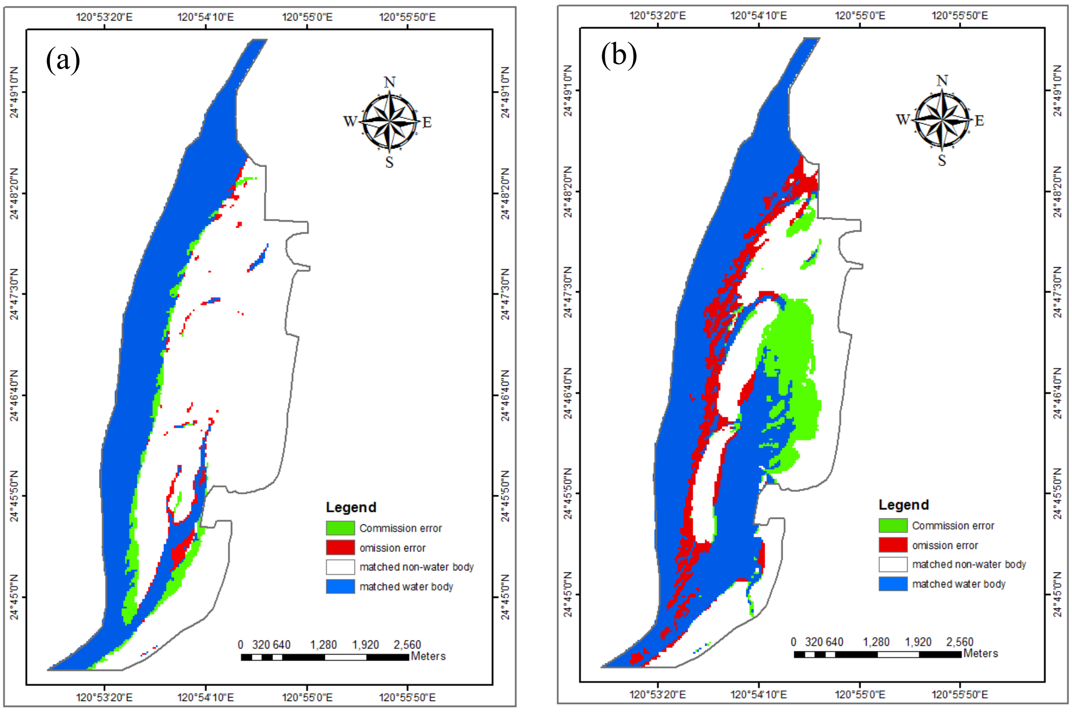


Figure 4. The evaluation map (a) Low Water Height case (b) Middle Water Height case

TABLE 2. THE ACCURACY ASSESSMENT

| WH Case | Commission Error (%) | Omission Error (%) | Overall Accuracy (%) | Kappa Coefficient |
|---|---|---|---|---|
| **Low** | 1.73 | 2.35 | 95 | 0.89 |
| **Middle** | 5.10 | 4.21 | 85 | 0. 73 |

## 4. Conclusion

This study investigates the potential of using the STAARCH (Spatial and Temporal Adaptive Algorithm for Mapping Reflectance Change) model to blend Landsat and Himawari-8 satellite images for effective sea level monitoring. The primary challenge in this type of research is the limitation of reference data, which can significantly affect the accuracy of image fusion and the subsequent monitoring processes. To address this issue, the study suggests that simulating reference data could be a valuable strategy, helping to mitigate data shortages and enhancing the model's performance. By integrating simulated data, the STAARCH model would have more reference points to accurately blend images, even when real-time data is scarce. Additionally, the application of Digital Elevation Models (DEMs) – based Nearest Neighbor (DNN) could be further improved by considering the use of DEMs and increasing the number of reference images in the process. DEMs would provide critical topographical information that could help refine the predictions, while incorporating more images as references would likely result in more precise image blending and a better understanding of sea level changes.

Moreover, the inclusion of simulated reference images directly into the STAARCH model could streamline the entire blending process, making it more efficient and adaptable to various environmental conditions. Temporal evaluation, which involves analyzing the performance of the model over time, could also serve as an additional validation index, providing a dynamic assessment of the model's accuracy across different timeframes. This would not only improve the reliability of the monitoring results but also offer a deeper insight into the temporal changes in sea levels. The next phase of this research will focus on identifying and utilizing a larger dataset of reference images to further enhance the simulation process, ensuring more accurate and consistent results. This approach could greatly improve the capability of STAARCH in handling large-scale, long-term monitoring of sea level variations, providing a robust tool for environmental and climate studies.

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