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Coastal Environmental Responses to Human Behavioral Changes during the COVID-19 Pandemic in South Korea

Seongsik Park,[1] Kyeongmin Kim,[2] and Kyunghoi Kim[3*]

[1]Research Center for Ocean Industrial Development, Pukyong National University, 45 Yongso-Ro Nam-gu, Busan 48513, Korea
[2]Faculty of Global Interdisciplinary Science and Innovation, Shizuoka University, 836 Oya, Suruga Ward, Shizuoka 422-8017, Japan
[3]Department of Ocean Engineering, Pukyong National University, 45 Yongso-Ro Nam-gu 48513, Busan, Korea

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The Coronavirus Disease (COVID-19) pandemic induced paradoxical changes in the coastal environment of South Korea. In this study, we found that following the outbreak, a significant reduction in tourist activity led to a 69.2% decrease in the amount of coastal waste. Conversely, an increased load of terrigenous organic matter (OM) from altered human activities resulted in higher concentrations of OM and chlorophyll-a in coastal waters. These changes led to contrasting effects on dissolved oxygen (DO) levels. To quantify these impacts, we employed satellite sensor data coupled with a machine learning model to spatially predict DO dynamics. In the deep offshore waters, enhanced photosynthesis from the phytoplankton bloom was predicted to have increased surface DO concentrations. However, in the shallow, semi-enclosed coastal waters, the increased OM load led to a decrease in DO concentration throughout the water column owing to heightened oxygen consumption. These findings underscore the complex and spatially varied responses of coastal ecosystems to widespread shifts in human behavior, highlighting the utility of advanced remote sensor technologies in coastal monitoring.

1. Introduction

The COVID-19 pandemic significantly altered human activities, leading to unforeseen and often contradictory consequences for coastal environments worldwide. On one hand, restricted tourism led to positive effects, such as a marked decrease in the amount of beach waste in Brazil and Ecuador.[(1,2)] On the other hand, the pandemic introduced new environmental pressures. For instance, the widespread use of quaternary ammonium surfactants (QASs) for disinfection resulted in the discharge of these potentially ecotoxicological chemicals into coastal ecosystems.[(3,4)]

*Corresponding author: e-mail: hoikim@pknu.ac.kr
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These shifts in human activity have also impacted the marine environment. Studies have shown varying effects globally, with chlorophyll-a (Chl.a) concentrations increasing in Kuwait Bay(5,6) but decreasing elsewhere, such as the Indian coast.(7) To date, however, a corresponding investigation of the coastal waters of South Korea has not been conducted. This represents a critical research gap, as changes in phytoplankton biomass directly affect dissolved oxygen (DO) levels, a key indicator of marine ecosystem health.(8,9)

Addressing this gap relies heavily on robust observational data. However, conventional water quality monitoring in South Korea, which largely depends on shipboard sampling and subsequent laboratory analysis, inherently suffers from low spatiotemporal resolution. To overcome this limitation, the application of spaceborne remote sensing technologies provides a powerful alternative.(10) Specifically, the Geostationary Ocean Color Imager (GOCI)—the world's first geostationary ocean color satellite equipped with a 500 m high-resolution sensor—offers unprecedented capabilities for monitoring dynamic coastal optical properties. GOCI provides multispectral remote sensing reflectance across various wavelengths.

Therefore, in this study, we investigated the pandemic's impact on the South Korean coast by analyzing changes in coastal waste, organic matter (OM), and Chl.a concentrations. Furthermore, we employed a machine learning model, trained with in situ data and satellite sensor observations, to spatially predict the resulting changes in DO concentration and demonstrate the efficacy of sensor-driven coastal monitoring.

2. Materials and Methods

2.1 Data

Data on coastal waste were sourced from the National Coastal Waste Monitoring program.(11) Eleven tourist-accessible stations (stCW1–11) were monitored bimonthly from 2018 to 2021 (Fig. 1). Surveys involved randomly sampling four 5 m sections within a 100 m stretch.

In situ concentrations of Chl.a and chemical oxygen demand (COD) were obtained from the Marine Environment Monitoring System.(12) Data from ten Environment Management Sea areas (stWQ1–10) were used, with values averaged for each area to serve as a representative figure. To analyze terrestrial inputs, COD concentrations from three major rivers(13) and monthly precipitation data from three corresponding stations were also incorporated.(14)

To supplement the in situ observations and provide broader spatial context, ocean color data were acquired from the GOCI satellite.(15) This included Chl.a and particulate organic carbon (POC) concentrations at a 500 m spatial resolution. Data were collected daily at 1 h intervals.

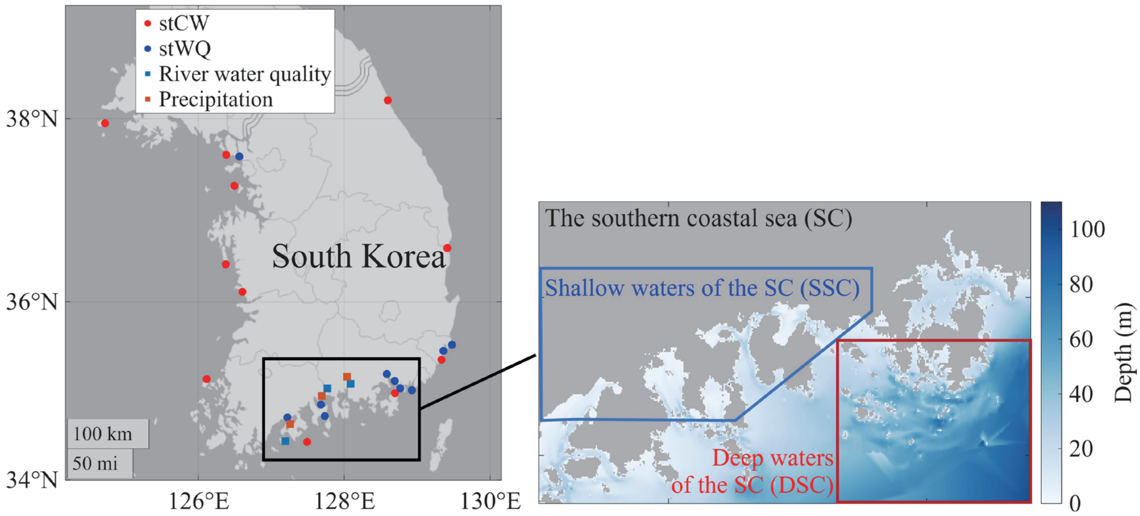

Fig. 1. (Color online) Location of the stations for coastal waste (stCW; red circle), coastal water quality (stWQ; blue circle), river water quality (blue square), and precipitation (brown square).

2.2 Statistical t-test

To compare the differences between the pre- and post-COVID-19 periods, statistical analyses were conducted on the basis of the data distribution. The normality of the data was evaluated using the Anderson–Darling test. For data satisfying the normality assumption or having a sufficiently large sample size ($n > 30$) to assume normality, a t-test was utilized. The equality of variances was assessed using the F-test; Student's t-test was applied when variances were equal, whereas Welch's t-test was used when the assumption of equal variances was violated.

2.3 Prediction of DO concentration

To predict the surface and bottom DO concentrations in the coastal sea, sea surface temperature data from the Aqua-MODIS satellite and ocean color data (e.g., remote sensing reflectance, diffuse attenuation coefficient, Chl.a, and POC) from the GOCI, observed between 2015 and 2021, were utilized. Fishery Environment Monitoring's DO concentration data were used as the response variable, with a total of 2374 data points.[16] The Gaussian process regression (GPR) model with an exponential kernel function was used to predict DO concentration. The GPR is a non-parametric model based on a kernel function, which is flexible to data and useful for complex data such as DO in marine environments. The GPR model was trained using 85% of the data, and its robustness was verified through a 10-fold cross-validation. The model's performance was evaluated using root mean square error (*RMSE*), coefficient of determination (R^2), and skill score (*SS*). The SS ranges from 0 to 1, with higher values indicating better agreement.[17]

3. Results

3.1 Changes in coastal waste

The amount of coastal waste at the monitored stations showed a significant decrease following the COVID-19 outbreak (Fig. 2). Before the pandemic, waste levels were notably higher during peak tourist months, with mean weights of 35.0 kg (May 2018), 42.4 kg (July 2018), and 26.4 kg (May 2019). However, after the pandemic's onset, these figures dropped sharply to 5.2 and 9.2 kg in May and July 2020, respectively. This reduction was statistically significant (Welch's t-test, $p < 0.05$), with the mean waste weight post-COVID-19 being 5.8 kg, a 69.2% decrease from the pre-pandemic period. Similarly, the average number of waste items collected fell by 26.6%.

3.2 Changes in coastal Chl.a and OM concentrations in August

Following the onset of the COVID-19 pandemic, significant increases in Chl.a and OM concentrations were observed in the coastal waters of South Korea. Satellite observations confirmed elevated concentrations of Chl.a and POC (Fig. 3). Specifically, in the southern coastal sea (SC), the mean Chl.a concentration increased 4.2-fold from 2.6 μg L^{-1} (*std.* = 3.8) before COVID-19 to 11.0 μg L^{-1} (*std.* = 17.0) after COVID-19. Correspondingly, the mean POC concentration doubled, rising from a pre-COVID-19 average of 246.7 to 484.1 μg L^{-1}. Both increases were statistically significant (Welch's t-test, $p < 0.05$). These findings were corroborated by in situ data from August 2020, which revealed that the mean Chl.a concentration was 154.2% higher than the 2007–2019 average, while the COD reached its highest level since 2007, marking an 83.7% increase from August 2019 (Fig. 4).

3.3 Prediction of change in DO concentration

The GPR model demonstrated high predictive accuracy (Fig. 5). For surface DO, the model achieved an *RMSE* of 0.57, an R^2 of 0.63, and an SS of 0.87. The bottom DO model performed similarly well, with an *RMSE* of 0.72, an R^2 of 0.69, and an SS of 0.90. The 10-fold cross-validation yielded a mean *RMSE* of 0.58 (*std.* = 0.03) and an R^2 of 0.58 (*std.* = 0.06) for surface DO, and a mean *RMSE* of 0.72 (*std.* = 0.07) and an R^2 of 0.69 (*std.* = 0.04) for bottom DO. The small standard deviations across the folds indicate that the models are unbiased toward specific data splits. Furthermore, the performance metrics from the test set fell within the standard deviation ranges of the cross-validation results, confirming the absence of model overfitting.

The validated model predicted contrasting DO responses between the deep offshore waters and the shallow coastal bays following the COVID-19 outbreak [Figs. 5(c) and 5(d)]. In the deep waters of the SC (DSC), the mean surface DO concentration was predicted to be 8.3 mg L^{-1}, an increase of 0.8 mg L^{-1} compared with the pre-COVID period. Conversely, in the shallow waters of the SC (SSC), DO levels decreased throughout the water column. Despite the increase in

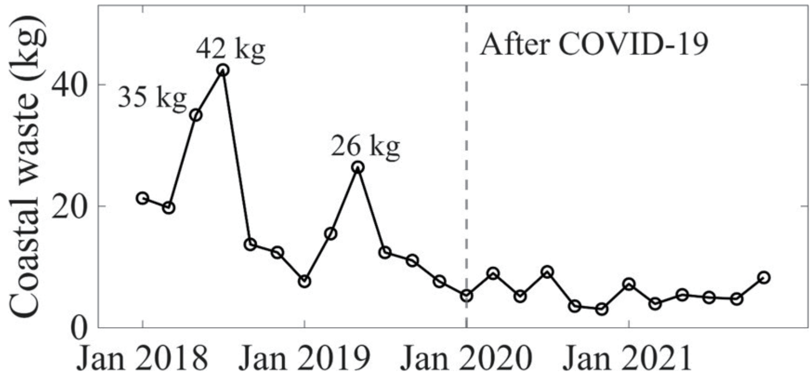

Fig. 2. Mean weights of coastal waste averaged at stCW1–11.

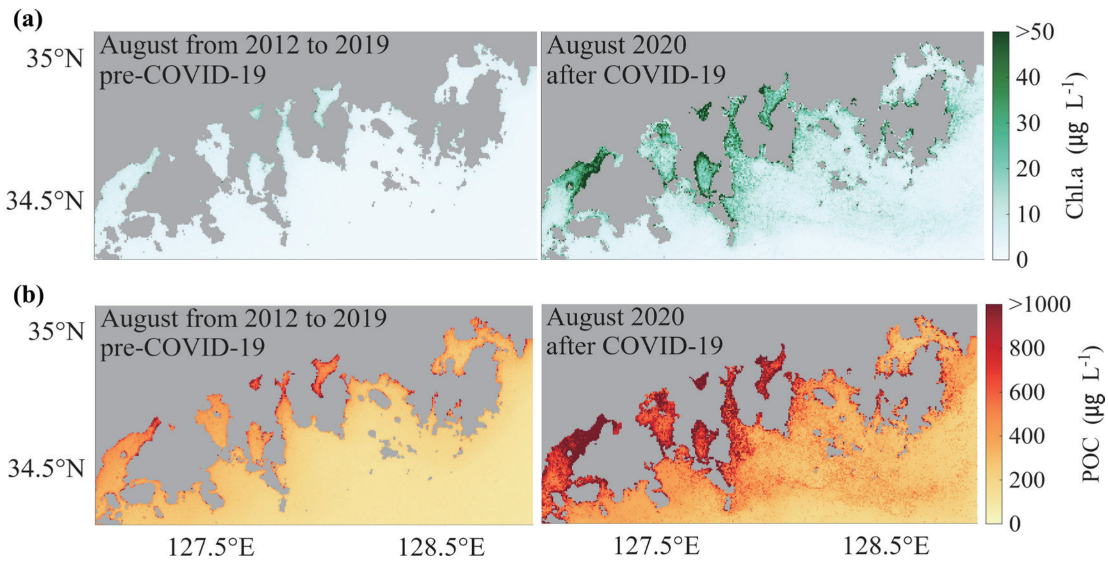

Fig. 3. (Color online) (a) Comparison of mean Chl.a concentrations in August from 2012 to 2019 (left; pre-COVID-19) and in 2020 (right; after COVID-19) along the southern coastal sea (SC). b is the same as a, but for POC.

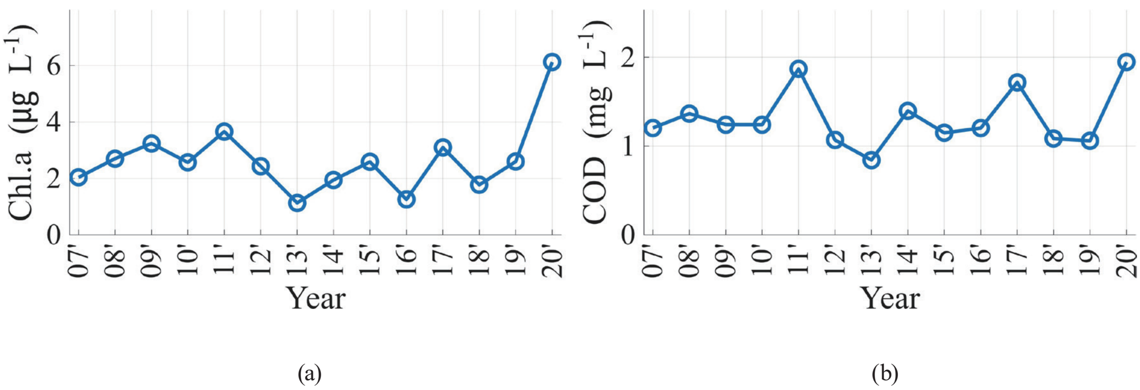

Fig. 4. (Color online) Mean concentrations of (a) Chl.a and (b) COD averaged at stWQ1–10 in Aug. 2007–2020.

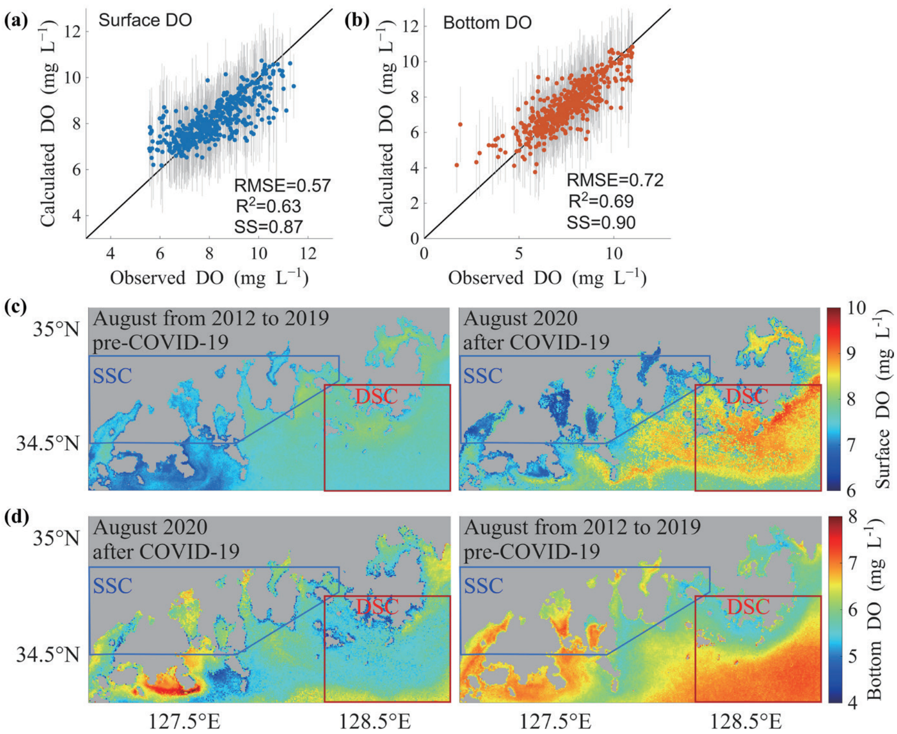

Fig. 5. (Color online) (a and b) Scatter plots showing the validation results for the (a) surface and (b) bottom DO prediction models. The grey vertical lines represent the 95% prediction intervals of the GPR model. (c, d) Spatial distribution maps of the predicted mean (c) surface and (d) bottom DO concentrations.

phytoplankton biomass, the mean surface DO was 0.3 mg L^{-1} lower and the mean bottom DO was 0.4 mg L^{-1} lower than pre-COVID averages.

4. Discussion

4.1 Environmental responses to changes in human activities

The decrease in the amount of coastal waste can be primarily attributed to the reduction in tourist activity, a major source of land-derived waste. While typhoons also contribute to marine-derived waste, only one small typhoon approached South Korea during the study period (July 2019), making it an unlikely factor.[18] In contrast, there was a considerable decline in tourism activity; the number of foreign tourists fell by up to 94.5% in 2020 and 2021, domestic tourism decreased by up to 34.7%,[19] and the number of visitors to 278 national beaches dropped by as much as 68.2%.[20] Therefore, the sharp decrease in the amount of coastal waste directly correlates with the reduced number of tourists.

The primary cause of the increase in coastal OM might be a larger influx of terrigenous OM. In August 2020, the mean COD concentration in the three major rivers reached 5.8 mg L^{-1}, representing a 61% increase compared with the 2007–2019 average (3.6 mg L^{-1}) (Fig. 6). Notably, this value exceeded the upper limit of the 95% confidence interval for the historical period (5.2 mg L^{-1}), indicating an anomalous surge. Conversely, this substantial OM increase was not driven

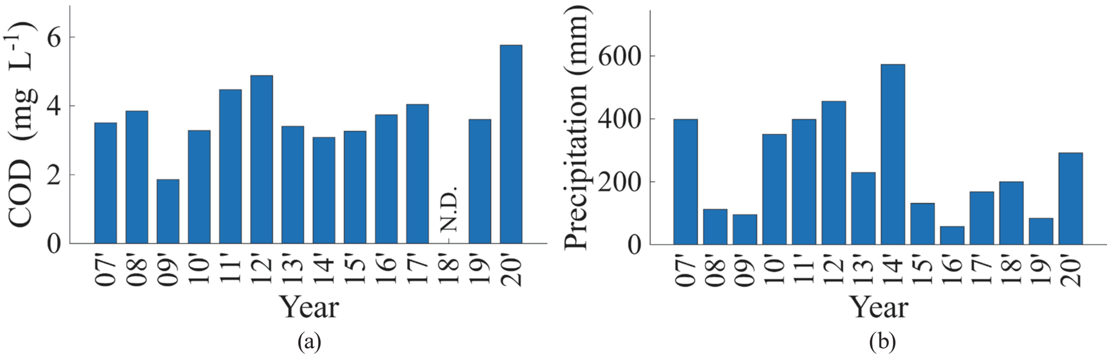

Fig. 6. (Color online) (a) Mean COD concentration averaged in the three major rivers and (b) mean precipitation in August 2007–2020.

by anomalous rainfall; the precipitation in August 2020 was 291.7 mm, showing only a 17% difference from the 2007–2019 average (250.2 mm) and remaining well within the upper limit of the historical 95% confidence interval (612.7 mm). Instead, the increased OM load appears to stem from pandemic-related lifestyle changes. With more people staying and working from home,(21) domestic and industrial water usage increased by 5.0 and 7.6%, respectively.(22) The sewage treatment load in the southern part of South Korea also increased by 9.0%.(23) A secondary contributing factor may be the widespread use of QASs for disinfection. During the pandemic, over half of the COVID-19 disinfectants on the EPA's recommended list contained quaternary ammonium compounds, with approximately 75% of these applications eventually released into sewers and wastewater treatment plants (WWTPs).(24) Indeed, observations in Athens, Greece, showed a 331% increase in the mass load of QAS entering WWTPs compared to pre-COVID levels.(25) This massive influx not only directly adds to the OM concentration but can also negatively impact OM-removing organisms in coastal ecosystems.(26,27) Ultimately, this enriched supply of OM fueled phytoplankton proliferation, resulting in the observed bloom and elevated Chl.a concentrations.

4.2 Spatial variations and mechanisms of DO responses

The increase in surface DO concentration in the DSC is attributed to enhanced photosynthesis driven by a massive phytoplankton bloom, where mean Chl.a concentrations were 5.4 times higher than pre-COVID levels. As phytoplankton are a primary source of marine oxygen, this finding aligns with other studies documenting elevated DO concentration during summer blooms.(8,9)

The decrease in DO concentration in the SSC is likely driven by an overriding increase in oxygen consumption rate owing to the higher OM load. Following the COVID-19 outbreak, the mean POC concentration in the SSC was 1047.4 μg L^{-1}, a 128% increase from the pre-COVID-19 level of 458.4 μg L^{-1} and 217% higher than the mean concentration in the DSC (330.2 μg L^{-1}) during the same period. This high POC level in the SSC highlights a massive oxygen-consuming organic matter pool. In addition, the geographic characteristics of the SSC—mostly semi-enclosed bays with low seawater exchange—exacerbate this effect by trapping OM and intensifying oxygen depletion from decomposition.(28) Therefore, the massive phytoplankton bloom in the SSC poses a long-term threat, as its eventual decay is expected to heighten the risk of hypoxia. Note that owing to the lack of direct in situ measurements of oxygen production and consumption rates, our interpretation relies on proxy indicators (Chl.a and POC), which remains a limitation of this study.

4.3 Efficacy of remote sensing applications and model limitations

In this study, we demonstrated the efficacy of remote sensing applications for monitoring complex coastal environments. Traditional in situ water quality monitoring relies on shipboard sampling and subsequent laboratory analysis, which inherently suffers from low spatiotemporal resolution and high cost. To overcome this, we utilized remote sensing technologies, specifically the GOCI sensor. By integrating these satellite sensor data with a machine learning framework trained on in situ observations, we successfully bridged the spatial gaps between monitoring stations. This approach highlights the vital role of remote sensing technology as a powerful tool for detecting and evaluating wide-ranging coastal environmental responses to sudden shifts in human behavior, such as the COVID-19 pandemic.

Despite these advantages, the GPR model utilized for DO prediction presents several methodological limitations that must be addressed in future research. First, while the model achieved high SS (0.87–0.90), the R^2 values were moderate (0.63–0.69), indicating that some variance in DO dynamics remains unexplained by the current input variables. Second, as a purely data-driven approach, the model lacks the explicit integration of physical and biogeochemical mechanisms, such as vertical mixing, water mass circulation, and detailed benthic respiration processes. Incorporating these mechanistic variables can further clarify the unexplained variance. Finally, the reliance on optical and thermal satellite sensors inevitably introduces missing data points owing to cloud cover and atmospheric correction challenges in highly turbid coastal waters. Future work should focus on coupling gap-filled, higher-resolution next-generation satellite data with advanced machine learning frameworks, thereby establishing a more robust coastal hypoxia forecasting system.

5. Conclusions

In this study, we revealed the paradoxical environmental impacts of the COVID-19 pandemic on South Korea's coastal ecosystems. While a sharp reduction in tourism activity led to a 69.2% decrease in the amount of coastal waste, pandemic-induced lifestyle changes intensified the influx of terrigenous OM, fueling a major phytoplankton bloom and causing contrasting DO responses depending on the geographical characteristics.

To quantify these spatially complex changes, in this study, we demonstrated the relevance of remote sensing technologies. Methodologically, integrating high-resolution remote sensing data with a machine learning framework successfully bridged the spatial gaps inherent in conventional in situ monitoring. This methodological implication highlights that sensor-driven models are highly effective tools for evaluating large-scale coastal dynamics in response to sudden anthropogenic shifts.

Despite these contributions, this study has clear limitations. The purely data-driven GPR model lacks the explicit integration of physical and biogeochemical mechanisms. Furthermore, the reliance on optical satellite sensors inevitably introduces missing data challenges owing to cloud cover and atmospheric correction in turbid coastal waters.

For future research, efforts should lead toward coupling gap-filled, higher-resolution next-generation satellite sensor data with advanced machine learning frameworks that incorporate mechanistic variables. Establishing this integrated, sensor-based forecasting system will be essential for managing coastal environments.

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About the Authors

Seongsik Park received his Ph.D. degree from Pukyong National University, South Korea, in 2025. He is currently a Ph.D. researcher at the Research Center for Ocean Industrial Development, Pukyong National University. His research interests range from coastal ecosystem to global climate variability with machine learning, 3-D flow modeling, ocean color data from satellite, and big data. (tjdtlr2565@hanmail.net)

Kyeongmin Kim received his Ph.D. degree from Hiroshima University, Japan, in 2021. He is currently an assistant professor at Shizuoka University. His research interests include the remediation of contaminated sediment, the recovery of valuable metals, the production of renewable energy, and the development of value-added materials.
(kim.kyeongmin@shizuoka.ac.jp)

Kyunghoi Kim received his Ph.D. degree from Hiroshima University, Japan, in 2009. He is currently a professor at Pukyong National University. His research interests range from coastal ecosystem to sediment microbial fuel cell, the remediation of contaminated sediment, waste recycling, and the prediction of marine environmental disaster. (hoikim@pknu.ac.kr)