BIO Web of Conferences **216**, 03002 (2026) https://doi.org/10.1051/bioconf/202621603002
SRCM 2025

Analysis of the Effects of Mesoscale Convective System on the Enhancement of Wind and Significant Wave Height in Indonesian Maritime Areas

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Abstract. Extreme weather characterized by strong winds and high waves poses serious risks to maritime safety in the Indonesian Maritime Continent. This study comprehensively quantifies the impact of Mesoscale Convective Systems (MCS) on Significant Wave Height and Wind Speed enhancements using Himawari-8/9 imagery and multi-mission satellite altimetry. By utilizing a robust 300-km spatial filter to isolate standalone offshore events, the research employs quantile-based and multi-classification approaches to evaluate spatial and temporal anomalies. The results indicate that ocean-atmosphere coupling is highly non-linear; multilinear regression models consistently failed to predict environmental anomalies (R^2<0.03). However, quantile analysis revealed critical threshold behaviors. Spatially, intense systems consistently drove higher positive anomalies. Significantly, a multi-classification interaction analysis demonstrated that the synergistic combination of the "strongest" MCS parameters (largest area, coldest temperatures, and highest top cloud) generated wave impacts eight times greater than the "weakest" systems. Conversely, temporal responses relative to a 24-hour baseline were complex and non-monotonic, suggesting the dominance of lag effects over instantaneous intensity. These findings provide quantitative evidence that MCS modulates air-sea interactions through complex non-linear mechanisms, demonstrating that operational maritime forecasting must adopt advanced probabilistic modeling rather than relying on simple linear parameterizations to capture these hazardous events.

1 Introduction

Indonesian Maritime Continent (IMC) represents one of the most convectively active regions on Earth, acting as a primary heat engine for the global atmospheric circulation [1]. Within this complex archipelago, Mesoscale Convective Systems (MCSs) which is known as organized clusters of thunderstorms with the scales extending hundreds of kilometers are one of the dominant weather phenomena, accounting for a significant proportion of total

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precipitation and extreme weather events over tropical regions [2]. In certain condition, MCS could produce a wide range damaging and widespread windstorms with the mean speed up to 23.6 ms^{-1} (45.9 knots), and responsible for the hazardous weather including tornadoes and flash floods which is called as Mesoscale Convective Complexes [3]. While the atmospheric characteristics of MCSs, such as their diurnal cycle, propagation, and rainfall contribution, have been extensively studied, most existing literature in the IMC has focused on precipitation dynamics, where MCSs are reported to contribute up to 45-70% of total rainfall in certain regions [4]. However, their coupling with the ocean surface dynamics remains a critical yet under-explored frontier. To date, quantitative assessments regarding the impact of MCSs on the sea surface state in Indonesian waters, particularly concerning the localized enhancement of wave height are virtually non-existent in the published literature. Specifically, the quantitative hydrodynamic response of the sea surface manifested as abrupt changes in Significant Wave Height (ΔSWH) and surface Wind Speed (ΔWS) to these intense convective forcing events is not fully quantified.

The interaction between MCSs and the ocean surface is governed by complex physical mechanisms. As deep convection develops, strong downdrafts transport high-momentum air from the mid-troposphere to the surface, creating divergent outflows and gust fronts [2]. These transient wind fields can generate steep and high-frequency wind waves that differ significantly from the background swell. However, standard meteorological and oceanographic models often struggle to capture the localized and transient nature of these interactions. Previous studies have predominantly relied on linear assumptions to scale storm intensity with environmental impacts. Yet, the hydrodynamic response to convection is likely highly non-linear [5], dependent on a synergistic combination of storm size, cloud-top height, and thermal intensity rather than any single parameter alone.

A major challenge in quantifying this impact lies in the observational gap. Unfortunately, In-situ buoy networks in the IMC are sparse due to very expensive funding and vandalism constraints, making it difficult to capture the spatial heterogeneity of MCS impacts over open waters. Furthermore, coastal effects often contaminate the signal of pure ocean-atmosphere coupling. This study focuses strictly on the offshore environment, following the findings of land-sea breeze circulation effects can extend up to 30 km from the coastline, this research isolates the analysis to open waters beyond this buffer zone to ensure that the observed anomalies are driven by convective systems rather than local land-sea breeze or thermal regimes [6].

A synergistic multi-mission satellite approach is used to detect MCS and its effects on sea. A high-resolution infrared imagery from Himawari-8/9 which is utilized with Advanced Himawari Imager (AHI) has capabilities to precisely resolve cloud parameters at a 2 km resolution to detect and characterize MCS properties which are MCS area (area), Cloud Top Temperature (CTT), and the estimation of Cloud Top Height (CTH) based on multichannel infrared difference [7]. A combination with sea state measurements from a constellation of altimeter satellites is used to gain the physical sea surface data (SWH and WS) with high accuracy and low bias in the open ocean [8].

The primary objective of this research is to comprehensively quantify the impact of MCSs on the enhancements of significant wave height (ΔSWH) and wind speed (ΔWS) in Indonesia offshore region. This study represents a significant advancement (state-of-the-art) in Indonesian maritime meteorology, as it is the first to explicitly decouple convective-driven wave anomalies from background conditions using a multi-mission satellite approach. We employ several methodologies that includes a spatial sensitivity analysis to empirically determine the effective radius of MCS influence, a dual-perspective analysis comparing spatial anomalies (inside vs. outside MCS) and temporal anomalies

(MCS vs. non-MCS baseline), and also a quantile-based multi-classification approach to decouple the effects of MCS size, intensity, and vertical extent. By moving beyond linear approximations, it aims to provide new insights into the of ocean-atmosphere interactions in the Maritime Continent.

2 Study Area and Data

2.1 Study Area

The geographical scope of this research encompasses the offshore waters of the Indonesian Maritime Continent, defined in Figure 1 within the coordinates of 93ºE to 147ºE longitude and 17ºS to 17ºN latitude. To ensure the analysis focuses strictly on open-ocean convective interactions and is unaffected by local diurnal wind regimes, a spatial filter was applied to mask coastal areas. Specifically, observations located within 30 km of the coastline which indicates that the influence of local land–sea breeze circulation were excluded from the dataset. By removing this coastal band, the study isolates the ocean-atmosphere coupling mechanisms driven by Mesoscale Convective Systems (MCSs) from near-shore local effects.

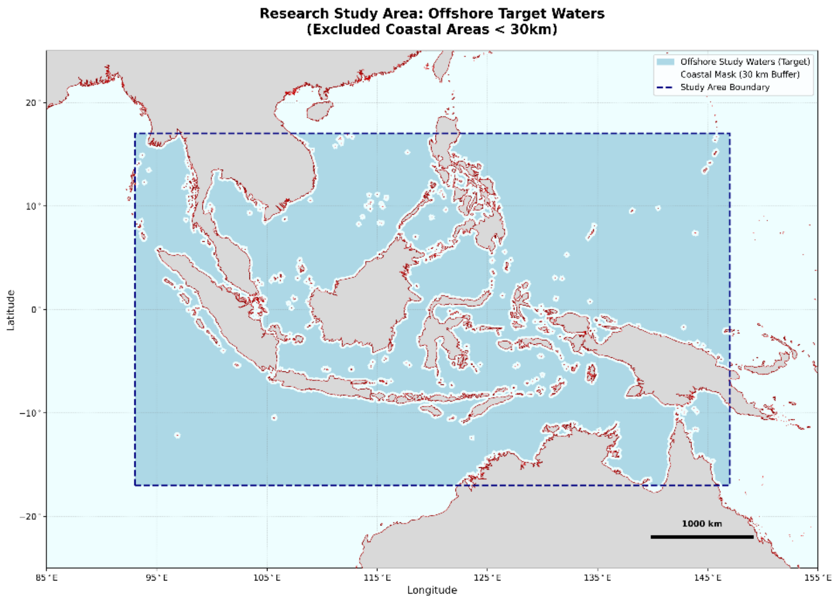

Fig. 1. Offshore study area for Indonesia Maritime Continent

2.2 Data Acquisition

A dataset that combines high-spatiotemporal-resolution geostationary satellite imagery with multi-mission satellite altimetry is used to gain the air-sea interaction effects. The observation period spans from January 1, 2021 to August 31, 2025, capturing a wide range of convective activity over the Indonesian Maritime Continent. By merging these complementary datasets, we aim to simultaneously resolve the atmospheric evolution of

Mesoscale Convective Systems (MCSs) and the corresponding variations in ΔSWH and ΔWS.

2.2.1 Himawari-8/9 Satellite Imagery

MCS detection and characterization were performed using data from the Advanced Himawari Imager (AHI) onboard the Himawari-8/9 satellites. it was identified using infrared Channel 13 (10.4μm) to delineate convective cloud clusters which was defined based on standard thresholds with a cloud-top brightness temperature (CTT) less than 235 K and a contiguous area of ≥ 10,000 km^2 [7, 10]. To determine the MCS's Cloud Top Height (CTH), the Split-Window technique was employed using the brightness temperature difference (BTD) between the water vapor absorption band (Channel 9, 6.9μm) and the clean infrared window band (Channel 14, 11.2μm) [9].

2.2.2 Multi-Mission Satellite Altimetry

Significant Wave Height (SWH) and surface Wind Speed (WS) data are served as the dependent variables for this analysis. These were derived from a comprehensive constellation of 10 satellite altimetry missions to ensure higher spatiotemporal coverage. The constellation includes: CryoSat-2, SARAL/AltiKa, Jason-3, Sentinel-3A, Sentinel-3B, CFOSAT, HY-2B, HY-2C, Sentinel-6 Michael Freilich, and SWOT. The data retrieval was automated using the Marine Copernicus Python module, ensuring access to standardized and quality-controlled oceanographic measurements.

3 Methodology

To evaluate the coupling between atmospheric convection and ocean surface dynamics, a multi-step processing workflow was developed from selecting potential MCS events which were identified and rigorously filtered to retain the only isolated systems occurring over the open sea (unaffected by sea-land breeze). These verified events were matched spatiotemporally with altimetry tracks to calculate the deviation of wind and wave parameters relative to background conditions. Finally, the relationship between MCS physical properties and the observed oceanic response was modeled using a combination of multiclassification techniques and multilinear regression.

3.1 Detection of Standalone Offshore MCS

Detection of Mesoscale Convective Systems (MCSs) was conducted using Cloud Top Temperature (CTT) data from the Himawari-8/9 Advanced Himawari Imager (AHI) using infrared bands where it has a 2 kilometers spatial resolution [7]. The MCS identification followed the objective threshold-based approach widely used in tropical convection studies, in which contiguous cold cloud-top areas with CTT values below 235 K (-38ºC) were classified as convective clusters with a minimum area exceeding 10,000 km² to ensure that the detected features represent truly MCSs [10]. This classification will create a polygon of MCS with an area more than 10,000 km^2.

Spatial independence was enforced to prevent the interaction signals from neighboring storms. The required separation distance was determined by analyzing the spatial decay of the wave impact relative to the MCS's size and shape. An iterative analysis was performed by creating multiple buffer zones around the MCS polygons, expanding from the cloud shield edge in steps of 50 km. For each buffer interval, the wave height enhancement (anomaly) was evaluated. The effective zone of influence was defined as the distance from the MCS edge where the wave anomaly ceases to be positive. The threshold identified through this analysis was subsequently used to filter the dataset, ensuring that only single (standalone) systems were located within each other's sphere of influence.

A land–sea mask derived from the Indonesian coastal polygon database was also applied to isolate the offshore MCSs. Only MCS entirely located over oceanic surfaces and showing no intersection with 30 kilometers from land were retained. This step ensures that the analyzed convective systems developed over the open sea and were unaffected by local wind regimes, such as land–sea breeze circulations. The resulting dataset represents standalone offshore MCS events, which provide more ideal basis for analyzing pure ocean–atmosphere coupling mechanisms.

3.2 Computation of Spatio-Temporal Differences of Altimetry Data

To evaluate the ocean surface response to MCS activity, a spatial and temporal (Spatio-Temporal) filtering procedure was implemented to extract relevant observations of significant wave height (SWH) and surface wind speed (WS) from multi-mission satellite altimetry data. Each MCS detection timestamp (T_{MCS}) was used as a temporal reference to define a ±30-minute observation window centered around the MCS occurrence time. Spatially, all altimetry measurements located within the geographical extent of the MCS polygon were selected to represent the “MCS area”. 150 km buffer zone surrounding the MCS polygon was defined to represent the background (non-convective) oceanic condition in the near-same time. This filtering method allows for the separation of altimetry-derived parameters between regions directly influenced by convective activity and adjacent unaffected ocean areas to capture the immediate mesoscale environment, often referred to as the 'near-environment', while avoiding contamination from far-field and macroscale synoptic features [11].

Following the spatio-temporal filtering process, two categories of differences were computed to quantify the oceanic response associated with MCS events which are spatial differences and temporal differences. The spatial difference was calculated as the deviation between the mean altimetry measurements inside the MCS polygon and those within the surrounding buffer zone. This parameter represents the instantaneous effect of convective forcing on the ocean surface relative to nearby unaffected regions.

The temporal difference was derived by comparing altimetry observations within the MCS polygon during its active phase (T_{MCS} ± 30 minutes) against measurements acquired over the same region during non-convective periods within ±24 hours of the event. This temporal comparison captures the time-evolving impact of MCS passage on wave and wind conditions. Both difference parameters were calculated for SWH and WS, resulting in a comprehensive dataset that describes the spatial and temporal variability of ocean surface responses to mesoscale convective activity.

3.3 Statistical, Quantile Based Multiclassification, and Multilinear Analysis

To assess the quantitative influence of MCS characteristics on ocean surface dynamics, a combination of descriptive statistics, quantile-based multiclassification analysis, and multilinear regression was applied.

3.3.1 Quantile-Based Classification

Prior to regression analysis, three fundamental MCS properties derived from satellite data namely MCS area (area), mean cloud-top temperature (CTT), and mean cloud-top height (CTH) were categorized based on its quartile distribution. The quartile method divides the dataset into four equal intervals (Q1–Q4), representing the increasing magnitudes of each parameter to generate meaningful clusters [12]. For example, Q1 represents the lowest 25% of observations (smaller, warmer, and lower MCSs), whereas Q4 represents the top 25% (largest, coldest, and highest systems). This classification allows the investigation of systematic trends in the enhancement of significant wave height (SWH) and surface wind speed (WS) according to MCS intensity levels. The mean and standard deviation of ΔSWH and ΔWS were computed for each quartile class to assess how stronger convective systems produce greater oceanic responses. The quantile-based analysis thus provides a discrete, physically interpretable framework prior to continuous regression modeling.

3.3.2 Multiclassification Analysis

In addition to individual quartile evaluations, a multiclassification approach was introduced to capture the combined influence of multiple MCS attributes. Each MCS event was assigned a categorical label based on the joint quartile class of all three parameters (area, CTT, CTH). For instance, a system classified as (Q4–Q4–Q4) represents a large, cold, and high-topped MCS, while (Q1–Q1–Q1) denotes a weakest convective system.

By grouping events according to these combined categories, the mean ΔSWH and ΔWS values were evaluated across all multiclass combinations. This enables identification of the most influential combination of MCS properties responsible for the greatest wave and wind enhancement. The results from this multiclassification were later compared to the multilinear model outcomes to validate and interpret the statistical dependencies identified by regression.

3.3.3 Multilinear Regression Analysis

To assess the quantitative influence of MCS characteristics on ocean surface dynamics, a multilinear regression analysis was applied by using MCS parameters derived from satellite data (area, CTT and CTH). These parameters respectively represent the horizontal extent, convective intensity, and vertical development of each system, while dependent variables were defined as the spatial and temporal differences of SWH and WS obtained from the altimetry filtering results. The relationship between these variables was expressed as:

$$\Delta Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \tag{1}$$

where ΔY corresponds to either ΔSWH or ΔWS. X_1, X_2, X_3 as independent variables (area, CTT, CTH). β_0 is the baseline value of ΔY. $\beta_1, \beta_2, \beta_3$ are coefficients of regression, representing the mean change in Y for a one-unit change in the corresponding X variable, while holding all other predictors constant. ϵ as the model error term (residual).

The model was applied to the four distinct datasets (spatial wave, temporal wave, spatial wind, temporal wind), while coefficient of determination (R^2) and Root Mean Square Error (RMSE) were used to assess model performance. R^2 was selected to quantify the proportion of variance in the oceanic response that can be explained by the linear combination of MCS parameters. It indicates the strength of the relationship and is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \quad (2)$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value from the regression model, and $\bar{y}$ is the mean of the observed data. A higher R^2 indicates a model that better fits the observed variability. Complementarily, the RMSE was used to measure the average magnitude of the model's prediction errors. Unlike R^2, RMSE provides an error metric in the same physical units as the dependent variable (meters for waves, m/s for wind), making it intuitive for interpreting the accuracy of the model estimates. Furthermore, RMSE penalizes larger errors more heavily, which is critical for assessing performance in extreme weather scenarios. It is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad (3)$$

This multilinear framework provides a statistical means to interpret how variations in convective system structure and intensity modulate the ocean surface, particularly in terms of wave height amplification and wind speed enhancement beneath MCS area.

3.4 Workflow Summary

The complete workflow is summarized in Figure 2. The methodology begins with the identification of MCS events using Himawari-8 AHI imagery, followed by spatial filtering to retain the only standalone offshore systems. These events are then matched with multi-mission altimetry data through a spatio-temporal filtering process to isolate measurements within and around MCS regions. Subsequent calculations of spatial and temporal differences enable the quantification of MCS-induced changes in sea surface conditions. Finally, the statistical and multilinear analyses integrate all derived parameters to evaluate the relationship between MCS properties and their corresponding impacts on wave and wind enhancement.

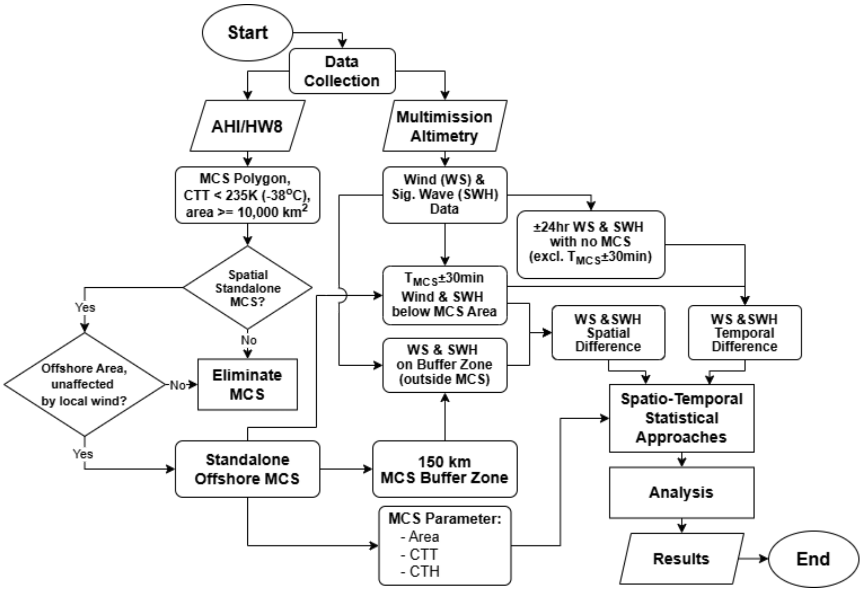

Fig. 2. Flow chart showing the process to analyze the effects MCS to wind and waves enhancements

This systematic approach allows for a comprehensive understanding of air-sea interactions driven by mesoscale convective systems, particularly in offshore environments that are minimally affected by local terrestrial dynamics.

4 Results and Discussion

Based on the sensitivity analysis described in methodology, the empirical assessment as shown in Table 1 revealed that the MCS-induced SWH amplification is confined within the average of 200 km buffer zone, after which the wave height difference (ΔSWH) values transition to negative. This suggests that the constructive influence of the MCS ceases beyond this threshold. To provide a robust safety margin and guarantee that the analyzed systems were fully isolated from neighboring convective influence, the exclusion radius was extended to 300 km.

Table 1. Significant wave height difference based on distance from MCS

Buffer Zone (km)	n-data	Mean ΔSWH	Std. Dev.
0-50	146	0.0865	0.2859
50-100	117	0.0621	0.2646
100-150	151	0.0611	0.2931
150-200	195	0.0120	0.2544
200-250	200	-0.0025	0.2339
250-300	86	-0.0227	0.2576

The interpretations of statistical analysis of MCS impacts on ΔSWH and ΔWS is structured into two primary methodologies which are a spatial analysis comparing conditions inside the MCS to a simultaneous external buffer zone and a temporal analysis comparing conditions during an MCS event to a baseline non-MCS period.

4.1 General Statistical Overview and Variability

A comparative descriptive analysis of all four study datasets presented in Table 2 gives a critical initial finding that MCS events are associated with an increase in both wave height and wind speed on average. Mean values in both spatial and temporal for ΔSWH (0.0369 m and 0.0351 m, respectively) and ΔWS (0.6434 m/s and 0.6013 m/s, respectively) are positive. However, the most prominent characteristic of the data is the extreme variability. Standard deviation for all four datasets is exceptionally large, often 4 to 5 times greater than its mean (e.g., ΔSWH mean 0.0369 vs. ΔSWH standard deviation 0.1666). This high variance indicates that while the average impact is positive, individual MCS events can produce a wide spectrum of effects, from strong localized suppression to significant amplification.

Table 2. Descriptive Statistics of Wave and Wind Difference under the existence of MCS

Analysis	Variable	n-data	Mean	Std. Dev.	Median (50%)	Min	Max
Spatial	ΔSWH	1951	0.0369	0.1666	0.0297	−1.4424	1.7158
Temporal	ΔSWH	1512	0.0351	0.2937	0.0225	−1.1523	1.8202
Spatial	ΔWS	1734	0.6434	1.4456	0.5028	−5.1916	11.7817
Temporal	ΔWS	883	0.6013	2.1988	0.3586	−6.9534	9.8016

A linear regression analysis performed using MCS parameter (area, CTT, CTH) to predict the magnitude of spatial and temporal anomalies for both SWH and WS gave the results that this regression analysis has the coefficient of determinations which are universally negligible, ranging from 0.0011 to 0.0204. This indicates that less than 3% of the variability in wind and wave anomalies can be explained by a simple linear combination of MCS size, temperature, and height. This lack of linear correlation is visually confirmed in Figure 3 (Comprehensive Scatterplot Matrix). The regression lines for all parameters are nearly horizontal, and the data points exhibit a high degree of dispersion (heteroscedasticity) rather than clustering around a trend line.

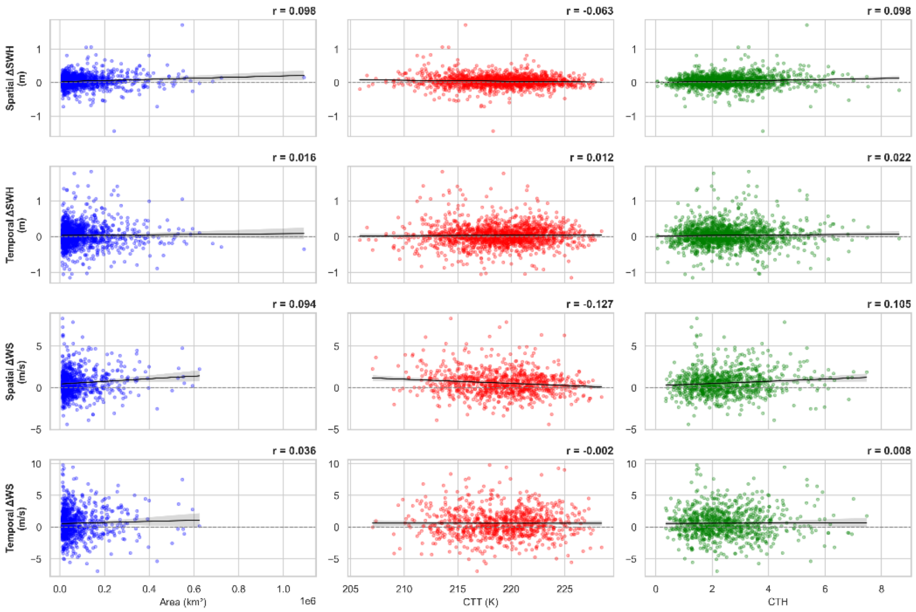

Fig. 3. Distributions of MCS parameter correlation to winds and waves enhancement

4.2 Justification for Quantile Based Analysis

A preliminary step using linear correlation analysis performed between three MCS parameters (area, CTT, CTT) and the dependent variables (ΔSWH and ΔWS) has revealed universally weak correlation coefficients for all parameters in both spatial and temporal contexts. The strongest Pearson correlation was merely 0.098 (area). This finding demonstrates that a simple multilinear regression model is fundamentally very weak and unsuited for capturing the complex and non-linear dynamics of MCS impacts to environmental changes. This weakness necessitates a more robust, non-parametric approach, justifying the use of the following quantile-based classification and interaction analysis to uncover the underlying trends.

4.2.1 Single-Parameter Quantile-Based Classification

To investigate non-linear trends, the mean impact of each MCS parameter was analyzed after stratification into quartiles (Q1: weakest/smallest, Q4: strongest/largest). The results for single-parameter quantile-based classification visualized in Figure 4 show the trends for every MCS Parameter in general. Spatial impact analysis between SWH and WS over MCS area vs. Buffer Zone has revealed several distinct trends where ΔSWH results a clear and positive monotonic relationship in both area and CTH which progressively increased from the smallest area (Q1: 0.013 m) to the largest (Q4: 0.061 m). Similarly, the impact from the lowest-top MCSs (Q1: 0.021 m) was three times weaker than that from the highest-top MCSs (Q4: 0.065 m). Meanwhile, the strongest trend of ΔWS had an inverse relationship with CTT. The coldest MCS produced the largest ΔWS (0.915 m/s), an effect that systematically weakened as cloud-top temperatures increased (Q4: 0.477). A positive (though non-monotonic) trend was also seen with CTH, where the highest-top storms (Q4: 0.864) had a significantly stronger impact than the Q2 (0.469). Spatially, the hypothesis that "stronger storms produce stronger impacts" holds true. Larger, higher, and colder (more intense) MCSs generate a significantly stronger wind and wave field within the storm's footprint compared to the immediate surrounding environment. This suggests that convective intensity and storm size are primary drivers of the spatial differential.

In sharp contrast, the temporal analysis (MCS vs. Non-MCS Baseline) revealed far more complex and often non-monotonic relationships. ΔSWH results the trends for area and CTT were non-linear. The impact peaked at Q3 (0.056) for area parameter and decreased slightly for Q4 (0.055). Meanwhile, U-shaped pattern was observed in CTT where the strongest impacts found at the extremes: Q1 (0.042) and Q4 (0.051). More chaotic trend is shown in ΔWS, no parameter produced a simple monotonic relationship. For instance, MCSs area impact was the weakest for Q2 (0.428), while CTT showed a no clear trend. The complexity of the temporal results suggests that the cumulative change from a baseline condition is not governed by peak intensity alone. Non-linear trends imply that different physical mechanisms might be at play during ±24 comparation.

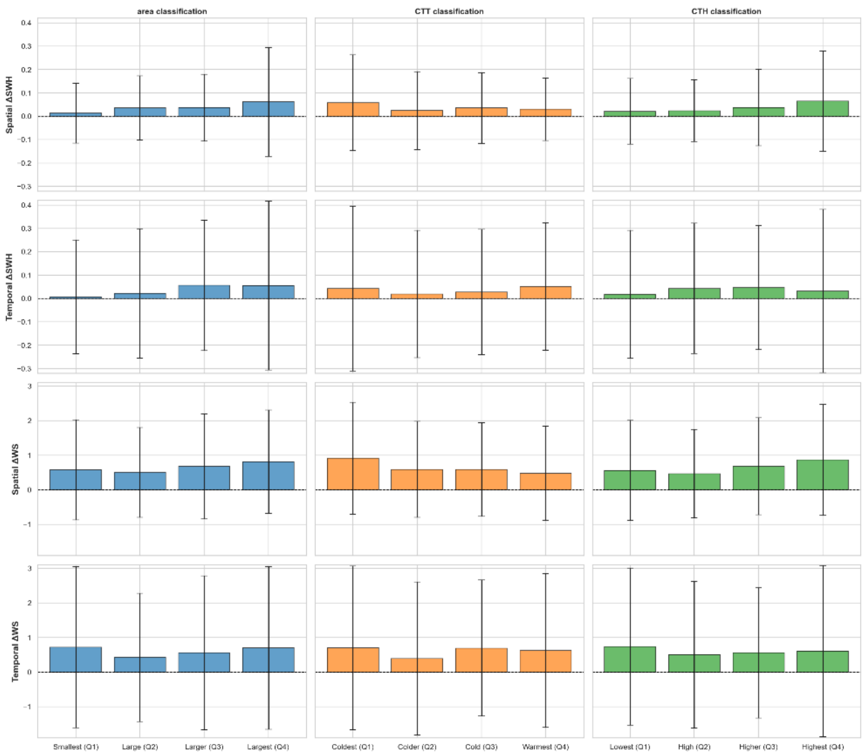

Fig. 4. Spatial and temporal Quantile based distributions of MCS parameter

4.2.2 Quantile-Based Multi-Classification Interaction Analysis

One of the core finding of this study emerged from the multi-classification analysis which evaluated the combined interaction of all three parameters by comparing the "Strongest" MCS combination (Q4 area, Q1 CTT, Q4 CTH) against the "Weakest" configuration (Q1 area, Q4 CTT, Q1 CTH). Table 3 shows the results where interaction effect of Spatial ΔSWH is dominant. A "Strongest" combination increases mean wave impact that is 8.0 times greater than the "Weakest" combination. This demonstrates that the synergistic combination of large area, high intensity (cold tops), and high altitude is the primary driver of extreme spatial wave generation. This "stronger is stronger" logic holds for Temporal ΔSWH (2.1x) and Spatial ΔWS (1.7x), confirming that the "Strongest" configuration is a robust generator of environmental impact.

A major anomaly was discovered for Temporal ΔWS. In this context, the "Strongest" MCS combination was less impactful than the "Weakest" combination, resulting in an inverse (0.8x) ratio. This is a profound finding, directly contradicting the logic of the other three analyses which strongly suggests that small, warm-topped, and low-altitude systems may induce a larger cumulative change in the wind field over time compared to non-MCS baseline. This could be due to longer durations, different propagation characteristics, or a dominance of large-scale stratiform wind fields rather than localized convective downdrafts.

Table 3. Multi-classification comparation of “Strongest” MCS against “Weakest” MCS

Variable	"Strongest"		"Weakest"		Impact Ratio
	n-samples	Mean	n-samples	Mean	
Spatial ΔSWH	165	0.0869 m	96	0.0108 m	8.0x
Temporal ΔSWH	126	0.0534 m	84	0.026 m	2.1x
Spatial ΔWS	148	0.9724 m/s	90	0.5636 m/s	1.7x
Temporal ΔWS	73	0.9899 m/s	51	1.2123 m/s	0.8x

4.3 Multilinear Regression Analysis

To investigate the potential for a direct linear prediction of environmental anomalies based on MCS parameters, a multiple linear regression (MLR) model was applied. The model utilized MCS parameter (area, CTT, CTH) as independent predictors for the spatial and temporal changes in SWH and WS. The statistical summary of the regression models is presented in Table 4.

Table 4. Multilinear regression equations analysis for Spatial and Temporal difference

Analysis Type	R^2	RMSE	Regression Equation
$\Delta SWH_{Spatial}$	0.0126	0.1743	$y=0.221+(1.07\times10^{-7})area-(0.0010)ctt+(0.0079)cth$
$\Delta SWH_{Temporal}$	0.0011	0.2938	$y=-0.481+(1.92\times10^{-8})area+(0.0023)ctt+(0.0078)cth$
$\Delta SWH_{Spatial}$	0.0204	1.4416	$y=8.799+(8.04\times10^{-7})area-(0.0383)ctt+(0.0418)cth$
$\Delta SWH_{Temporal}$	0.0015	2.1989	$y=0.041+(1.12\times10^{-6})area+(0.0025)ctt-(0.0274)cth$

The primary finding from this analysis is the negligible predictive power of the linear models across all scenarios. The Coefficient of Determination (R^2) values are consistently below 0.03, indicating that less than 3% of the variance in ΔSWH and ΔWS can be explained by a linear combination of MCS physical parameters. This lack of linear correlation is consistent with previous studies suggesting that convective-scale interactions are inherently non-linear and governed by stochastic processes rather than simple scaling laws [5]. The spatial models performed marginally better than the temporal ones, though still poorly. Model achieved the highest R^2 (0.0204) for ΔWS. The signs of the coefficients in the spatial equations align with physical expectations where negative coefficient for CTT and positive coefficient for area and CTH suggest that colder, wider and higher convective clouds tend to drive stronger positive anomalies. However, the high RMSE (1.44 m/s for wind) relative to typical anomaly values confirms that this linear trend is overwhelmed by other variability. The temporal models showed essentially no linear correlation with R^2 values approaching zero (ΔSWH: 0.0011, ΔWS: 0.0015). The regression coefficients for CTT even flipped to positive values in temporal models, contradicting the expected thermodynamic relationship where colder storms are typically more intense. This near-zero correlation in temporal models likely reflects the mismatch between instantaneous satellite snapshots and the delayed response of the ocean surface, a phenomenon known as the 'fetch-limited' or 'time-lagged' growth of waves under transient storm forcing [13].

The failure of the MLR analysis to yield significant correlations provides a crucial insight into the ocean-atmosphere coupling mechanism during MCS events. It demonstrates that the impact of an MCS on the sea surface does not follow a simple scaling law. Literature on tropical convection suggests that environmental responses often exhibit "threshold behaviors" where significant impacts only materialize once a storm reaches a critical level of organization or intensity [14]. A storm that is twice as large or twice as cold does not linearly produce twice the wave height or wind speed anomaly. Instead, the interaction is likely characterized by threshold behaviors and complex non-linear synergies between storm size, intensity, and the background environmental state. As noted by [15], the momentum transfer from convective downdrafts to the sea surface is highly dependent on the stability of the boundary layer, which cannot be captured by cloud-top parameters alone. Consequently, relying solely on linear parameterizations to predict MCS impacts in marine forecasting would be insufficient.

5 Concluding Remarks

This study provides a comprehensive quantification of the ocean surface response to Mesoscale Convective Systems (MCSs) in the Indonesian Maritime Continent. By integrating geostationary imagery with multi-mission satellite altimetry, we establish that the hydrodynamic impact of MCSs on Significant Wave Height (ΔSWH) and Wind Speed (ΔWS) is inherently non-linear and governed by complex interaction effects. Our findings demonstrate that simple linear models are insufficient for predicting convective-driven sea state anomalies, as extreme responses depend on a synergistic combination of storm size, intensity, and vertical development rather than single parameters alone.

Furthermore, the study highlights a significant divergence between instantaneous spatial anomalies and time-lagged temporal evolutions. These insights underscore the necessity for operational forecasting systems to shift from linear parameterizations toward non-linear, probabilistic, or machine-learning-based frameworks to accurately mitigate maritime hazards associated with deep convection in tropical offshore environments.

The Acknowledgements: The authors would like to express their sincere appreciation to Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) for providingmdata and necessary facilities that supported this research.
Fundings: This research was financially supported by the Indonesia Endowment Fund for Education (LPDP).
Data availability: This study has been conducted using E.U. Copernicus Marine Service Information; 10.48670/moi-00176; 10.48670/moi-00183

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