frontiers | Frontiers in Marine Science

TYPE Original Research
PUBLISHED 20 March 2025
DOI 10.3389/fmars.2025.1536014

Sensitivity analysis of drag coefficient and length scale of wind influence on tropical cyclone intensity change using net energy gain rate

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RECEIVED 28 November 2024
ACCEPTED 03 March 2025
PUBLISHED 20 March 2025

CITATION
Kim S, Lee W, Won S, Kang H-W, Kim KO and Kang SK (2025) Sensitivity analysis of drag coefficient and length scale of wind influence on tropical cyclone intensity change using net energy gain rate.
Front. Mar. Sci. 12:1536014.
doi: 10.3389/fmars.2025.1536014

Predicting tropical cyclones (TC) rapid intensification (RI) is one of the most significant challenges. This study refines the Net Energy Gain Rate (NGR) metric to improve TC intensity predictions, focusing on uncertainties in the drag coefficient (C_d) at extreme wind speeds and the effective length scale of TC-induced momentum transfer to the ocean (R_w). Using data from the western North Pacific basin (2004–2021), we conducted sensitivity analyses with four C_d parameterizations (increasing, decreasing, constant, and control) and varied R_w from 0.5 to 4 times the radius of maximum wind (R_{max}). Results indicate that R_w $=1R_{max}$ consistently yields the highest correlation coefficient between NGR and intensity change in 24-hour among all combinations, especially for strong TCs (Category 3 or higher). Among the C_d parameterizations, the scenario where C_d decreases at wind speeds exceeding 50 m s^{-1} showed superior performance in capturing intensity changes. Multi-linear regression models incorporating NGR, prior 12-hour intensity changes, and vertical wind shear confirmed that decreasing C_d at R_w=$1R_{max}$ provides the most reliable predictions, achieving the highest prediction performance in the TC intensity change in 24-hour. These findings underscore the importance of accurately representing C_d behavior under extreme wind conditions and precisely defining R_w to enhance the predictive skill of NGR-based TC intensity forecasts.

KEYWORDS
drag coefficient, tropical cyclone intensity change, rapid intensification, air-sea interactions, net energy gain rate

1 Introduction

The rapid intensification (RI) of tropical cyclones (TCs)—defined as an increase in wind speed of at least 30 knots within 24 hours—remains one of the most significant challenges in weather forecasting. Accurate predictions of these sudden surges in intensity are crucial for issuing timely evacuation orders, implementing disaster response measures, and minimizing damage to both infrastructure and human life (Kaplan and DeMaria, 2003; Sampson et al., 2011; Rappaport et al., 2012). With the growing destructiveness of tropical cyclones in a warming climate (Emanuel, 2005; Mendelsohn et al., 2012; Liu et al., 2020), coupled with their shifting genesis and maximum intensity to higher latitudes (Kossin et al., 2014; Daloz and Camargo, 2018; Sun et al., 2019; Shan and Yu, 2020; Feng et al., 2021; Studholme et al., 2022), reliable RI predictions have become more critical than ever for coastal populations around the world.

Despite advancements in dynamic and statistical TC prediction skills, including artificial intelligence techniques such as machine learning algorithms and neural networks (Atlas et al., 2015; Kim et al., 2018; Chen et al., 2020; Kumar et al., 2023; Wang et al., 2023; Majumdar et al., 2023), improvements in forecasting TC intensity have been modest (Rappaport et al., 2012; DeMaria et al., 2014; Balaguru et al., 2018; Cangialosi et al., 2020). One of the primary sources of intensity forecast errors lies in the challenges associated with predicting RI. The complexity of RI processes arises from intricate interactions between oceanic and atmospheric conditions, including sea surface temperature, ocean heat content, vertical wind shear, mid-level moisture, and internal storm dynamics (Kaplan et al., 2015). While advancements in modeling techniques have somewhat improved RI forecasts, accurately capturing the timing and magnitude of these events remains challenging due to their highly dynamic and nonlinear nature. As a result, significant gaps persist in RI prediction, with current models still struggling to identify and fully understand the key factors that drive its occurrence and intensity (DeMaria et al., 2014; Cangialosi et al., 2020; Huang et al., 2021; Jiang et al., 2022).

The surface heat flux between the ocean and atmosphere—particularly the latent heat flux—is a key energy source for TC development (Emanuel, 1986; Bryan, 2012; Green and Zhang, 2014; Zhang and Emanuel, 2016). Among these, the latent heat flux is dominant in TC intensification and is significantly affected by TC-induced sea surface cooling (SSC). TC-induced SSC is determined by the ocean's initial thermal structure and the total amount of momentum transferred from the TC's winds to the ocean. Greater momentum transfer leads to deeper vertical mixing, which brings cooler water to the surface and intensifies SSC (Price, 1981; Sanford et al., 2011). The total momentum transfer is controlled by wind stress and the duration of the TC's influence over a given area, itself dictated by the storm's translation speed and the effective radius of its winds (R_w). While numerous studies have examined the role of translation speed in SSC, relatively few have focused on the critical impact of R_w (Li et al., 2024). As the length scale over which wind stress effectively transfers momentum to the ocean, R_w influences the TC's residence time over specific ocean regions and consequently affects the magnitude of SSC. Therefore, a targeted sensitivity analysis of R_w is essential for accurately representing ocean conditions during a TC's passage.

The drag coefficient (C_d) is a critical factor in determining wind stress, as it directly controls the efficiency of momentum transfer from the wind to the ocean. A higher C_d increases wind stress, amplifying the force exerted on the ocean surface. This enhanced wind stress leads to deeper vertical mixing and enhanced SSC, significantly influencing the energy available for a TC to intensify. Additionally, increased C_d results in greater frictional dissipation in the atmospheric boundary layer, dissipating the TC's energy and directly affecting its intensification process (Kim et al., 2022; Lee et al., 2022). Given its significant impact on both processes, accurate parameterization of C_d is crucial for improving TC intensity predictions. Generally, C_d increases with wind speed under low to moderate conditions—up to approximately 30 m s^{-1}—but decreases or levels off at higher wind speeds (Powell et al., 2003; Jarosz et al., 2007; Edson et al., 2013; Donelan, 2018; Richter et al., 2021). However, due to limited observational data under extreme wind conditions, conflicting results persist regarding C_d's behavior at extreme wind speeds exceeding 50 m s^{-1} (Richter et al., 2016). Some studies suggest that C_d decreases at these high wind speeds (Richter et al., 2021; Lee et al., 2022), while others report that it increases (Soloviev et al., 2014; Donelan, 2018), levels off (Takagaki et al., 2012; Wang et al., 2024), or shows no clear trend (Bell et al., 2012). This uncertainty poses a significant challenge for accurately modeling air-sea interactions and predicting TC intensity, especially during RI events.

The Net Energy Gain Rate (NGR), introduced by Lee et al. (2019), builds upon the maximum potential intensity (MPI) framework (Emanuel, 1988) to quantify the energy exchange between the ocean and the atmosphere during TCs. In their study, they utilized a realistic wind-dependent parameterization of C_d, suggested in previous observation-based research, to calculate frictional dissipation. Additionally, instead of using sea surface temperature, they employed depth-averaged ocean temperature to compute the energy generation term, allowing NGR to provide a more accurate representation of TC energy dynamics. This metric strongly correlates with 24-hour TC intensity changes, outperforming traditional predictors like MPI and Intensification Potential (POT) in forecasting intensity changes (Lee et al., 2019). Moreover, statistical model tests incorporating NGR demonstrate significantly improved predictive skills for RI, highlighting its potential as a valuable tool for enhancing TC intensity forecasts (Kim et al., 2024).

Building upon the challenges in accurately modeling air-sea interactions and predicting TC RI, this study aims to enhance the reliability of TC intensity forecasts by refining NGR metrics. Specifically, we address two critical uncertainties that may impact the predictability of NGR: $R_w$and the relationship between C_d and high wind speeds exceeding 50 m s^{-1}. Firstly, due to the uncertainty surrounding C_d at extreme wind conditions, we calculate four different NGR values, each considering the various possible behaviors of C_d under extreme winds. This method addresses existing uncertainties in the frictional dissipation and representation of wind stress, as well as its effects on the flux exchanges. Secondly, we conduct a comprehensive sensitivity analysis of R_w to systematically evaluate its impact on TC-induced vertical mixing and the predictability of NGR. This aims to optimize the NGR calculations to capture oceanic conditions more accurately during the TCs. The data and methodologies employed in this research are detailed in Section 2. Section 3 examines the effects of the four different C_d parameterizations on NGR and conducts a sensitivity analysis of R_w. Finally, Section 4 presents our discussions and summarizes the study's key findings.

2 Data and methods

2.1 Data

This study used version v04r01 of the International Best Track Archive for Climate Stewardship (IBTrACS) dataset (Knapp et al., 2010). The best track data include various information derived from all forecasting agencies, such as the geographic locations of TC centers, maximum sustained wind speed, minimum central pressure, translation speed, radius of maximum wind, and other relevant parameters. We analyzed data provided by the Joint Typhoon Warning Center from 2004 to 2021. In this study, TCs are defined as storms with a maximum surface wind speed of over 34 knots occurring in the western North Pacific (WNP) basin, which is the region between 0°–60°N latitude and 100°–180°E longitude. To simplify the analysis and avoid possible uncertainties introduced by interpolation, we used the 6-hour interval track data. Cases in which the TC was within 259 km of the coastline—corresponding to the global mean radius of 34kt winds plus one standard deviation, based on a statistical analysis of TCs from 2001 to 2017 (Kim et al., 2022)—were excluded from the analysis to minimize the influence of topography.

Several oceanic and atmospheric variables were examined to calculate the NGR and mixing depth for individual TCs in the WNP. Sea surface temperature (SST), DAT, and ocean temperature and salinity profiles were obtained from the Hybrid Coordinate Ocean Model (HYCOM) Navy Coupled Ocean Data Assimilation (NCODA) nowcast/forecast system provided by the Naval Research Laboratory. The HYCOM-NCODA data used include daily outputs for 2004–2018 and 6-hourly outputs for 2019–2021. The HYCOM salinity and temperature profiles below the water surface were interpolated at regular depth intervals of 1 m between 1 m and 500 m. The NGR values were obtained based on Emanuel's 'pcmin.f' Fortran function, which is available online (pcmin_2013.f). The atmospheric variables required to calculate NGR—air temperature, relative humidity, and mean sea level pressure—were obtained from the Global Forecast System (GFS) analysis data provided by the NCEP. The GFS data have spatial resolutions of 1° × 1°for 2004–2016 and 0.5° × 0.5°for 2017–2021, with 6-hour temporal resolution. All atmospheric and oceanic variables were averaged within a radius of 200 km from the storm center using prestorm conditions (3 days prior) (Lee et al., 2019, 2022; Kim et al., 2022, 2024; Moon et al., 2022).

In this study, our ultimate goal is to develop an operational model for predicting TC RI using GFS forecast fields as input. To achieve this, we have trained our model with GFS analysis fields. Notably, the 6-hourly gridded analysis data provided by NOAA's NCEI has been available only from March 2004 onward. Consequently, our overall analysis period was chosen to align with these data availability constraints.

2.2 Net energy gain rate

NGR measures the difference between the enthalpy flux out of the sea surface (G) and the surface frictional dissipation of energy (D) in the atmospheric boundary layer, which is defined as:

$$\mathrm{NGR} = G - D = \frac{DAT - T_0}{T_0} C_k \rho V_s (k_0^* - k) - C_{d(v_s)} \rho V_s^3$$

where DAT is the depth-averaged ocean temperature, T_0 is TC outflow temperature determined by the atmospheric vertical profile, C_k is enthalpy exchange coefficient, ρ is the air density, V_s is surface wind speed, k_0^* is saturation enthalpy of the sea surface, k is surface enthalpy in the TC environment. DAT is computed as:

$$\mathrm{DAT} = \frac{1}{d} \int_{-d}^{0} T_i(z) dz$$

where T_i is the initial ocean temperature, and d is the mixing depth discussed in Section 2.4.

2.3 Drag coefficient parameterizations for extreme winds

Owing to uncertainties in C_d under extreme wind conditions (Powell et al., 2003; Donelan, 2018; Soloviev et al., 2014; Richter et al., 2021; Lee et al., 2022; Wang et al., 2024), we evaluate four different parameterizations that reflect possible behaviors of C_d for winds above 50 m s^{-1}. Following Kim et al. (2022), we considered four different behaviors of the drag coefficient C_d: three experimental C_d fittings and one control fitting. All three experimental C_d fittings are the same up to 50 m s^{-1} but show different trends after 50 m s^{-1}: increasing (CD_IC), decreasing (CD_DC), and constant (CD_CN) (Figure 1). These C_d fittings (CD_IC, CD_DC, CD_CN) range from 1×10^{-3} to 2.5 $\times 10^{-3}$ for wind speeds below 50 m s^{-1}, which are within the range of field and experimental study results (Powell et al., 2003; Jarosz et al., 2007; Edson et al., 2013; Soloviev et al., 2014; Donelan, 2018; Richter et al., 2021). In the control experiment (CD_DN), we used the C_d from Donelan et al. (2004), where C_d increases up to 33 m s^{-1} (consistent with the other three experimental C_d fittings) but saturated beyond 33 m s^{-1}.

2.4 Depth of TC-induced mixing and sensitivity analysis of R_w

To estimate the depth of TC-induced mixing (d), we use Price (2009) method, which links vertical turbulent mixing to the TC wind forcing under the criterion that the bulk Richardson number of the surface mixed layer should not be less than 0.6 (Price, 1981):

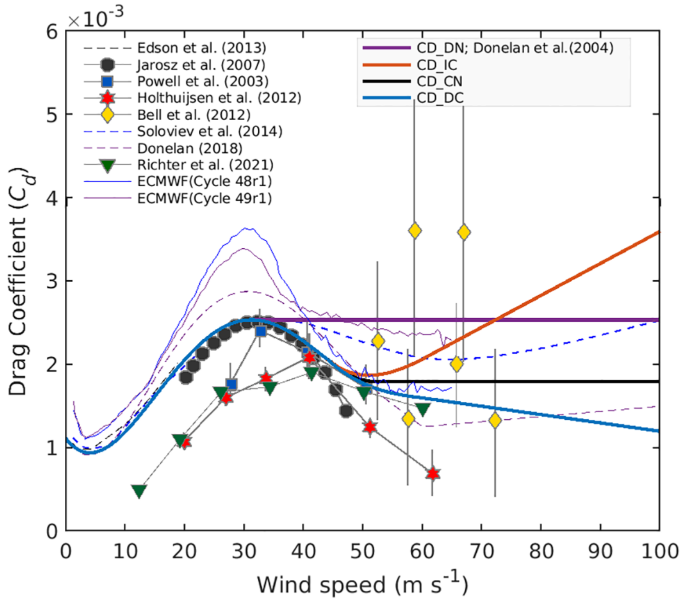

FIGURE 1
Comparison of drag coefficients (C_d) parameterizations presented in previous studies as a function of 10-meter wind speed. The C_d parameterizations used in this study are highlighted in the legend with gray shading.

$$\frac{g[\rho(z=-d) - \frac{-1}{d}\int_0^{-d}\rho(z)dz]d}{\rho 0(\frac{\tau}{\rho_0 d}\frac{R_w}{U_h}S)^2} \geq 0.6$$

where g is the acceleration due to gravity, $\rho(z)$ is the density profile derived from ocean temperature and salinity profiles, $\rho0$ is the reference density, τ is the wind stress, S is the non-dimensional storm speed (S = 1.2) (Price et al., 1994), and R_w/U_h represents the TC's residence time over a given location. In many studies, R_w/U_h is taken as $4R_{max}/U_h$ (Price, 2009; Pun et al., 2019; Kim et al., 2022; Moon et al., 2022), assuming the ocean is mixed by the time the TC has completely passed. However, Because the ocean encountered by the TC during its intensification is still in the process of mixing and not yet fully mixed, using this method may lead to an overestimation of SSC. To address this issue, we conducted sensitivity experiments by varying R_w from $0.5R_{max}$ to $4R_{max}$ increments of $0.5R_{max}$. This systematic approach identifies the R_w value that yields optimal NGR-based prediction of 24-hour intensity changes, especially during RI events.

3 Results

3.1 Sensitivity analysis of C_d parameterizations and R_w values

To investigate how different C_d parameterizations and values of R_w affect 24-hour TC intensity changes, we performed a series of sensitivity analyses using four different C_d parameterizations—CD_IC, CD_DC, CD_CN, and CD_DN—along with varying values of R_w(from 0.5 to 4 times R_w). For each combination of C_d and R_w, we calculated the NGR, and analyzed the correlation coefficients between NGR and observed 24-hour changes in TC intensity. Because the four C_d parameterizations show significant divergence for wind speeds above 50 m s^{-1}, we separately considered all TCs (tropical storm or higher) and strong TCs (Saffir-Simpson Category 3 or higher).

Figure 2 compares the correlation coefficients between NGR and observed 24-hour intensity changes across the tested R_w and C_d combinations. Although some C_d parameterizations achieve relatively high correlations at R_w = 0.5 R_w, the highest correlation among all combinations appears at R_w = 1 R_w, especially for stronger TCs (≥ Cat3). Among the C_d parameterizations, CD_DC and CD_CN consistently exhibit higher correlations, whereas CD_IC (Figure 2, red solid line) generally shows the weakest correlation across all R_w values—even lower than the control (CD_DN; Figure 2, purple solid line).

In strong TCs, where most RIs occur (Lee et al., 2016), CD_DC showed the highest correlation coefficients in the all R_w range. CD_DC, where C_d decreases after 50 m s^{-1}, notably shows improved performance in capturing TC intensity changes, particularly strong TCs experiencing RI events. This aligns with the findings of Lee et al. (2022), which demonstrated that a decreasing C_d parameterization significantly reduces the underestimation of TC intensity in numerical models and provides the best prediction performance for intense storms. This agreement further underscores the importance of accurately parameterizing C_d for capturing RI dynamics.

Figure 3 illustrates the effect of R_w values and C_d parameterizations on the d and DAT for TCs of tropical storm intensity (≥ TS) and strong TCs (≥ Cat 3). The wind stress is proportional to the C_d times the wind speed squared (Rieder et al.,

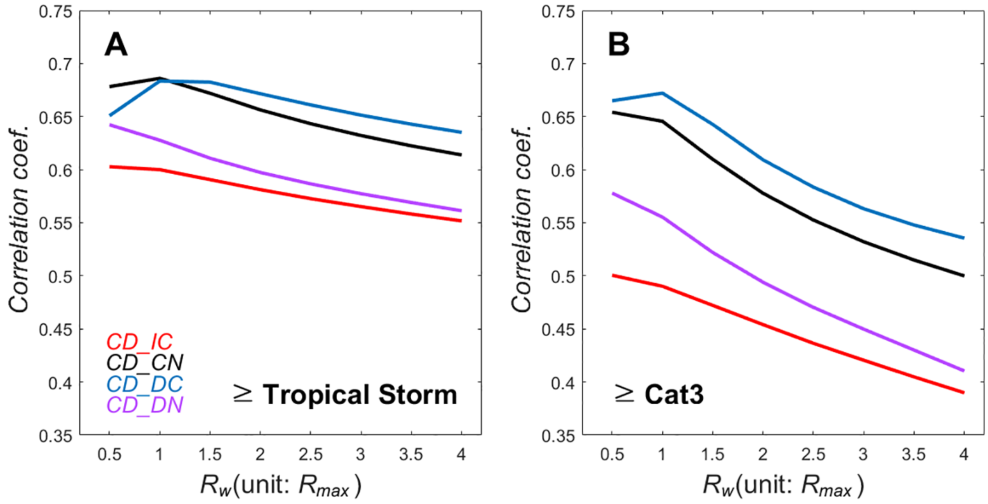

FIGURE 2
Comparison of correlation coefficients between NGR and the 24-hour intensity change based on different C_d fittings as a function of R_w (in units of R_{max}). **(A)** shows results for TCs at tropical storm intensity or higher (≥ Tropical Storm), while **(B)** represents those rated at category three or higher on the Saffir-Simpson scale (≥ Cat 3).

1994; Powell et al., 2003); this indicates that decreased or constant C_d under high wind reduces the momentum flux into the ocean compared to increased C_d, inhibiting vertical mixing of the upper ocean. Consequently, SSC in the CD_DC and CD_CN experiments is reduced, resulting in a higher DAT than CD_IC and CD_DN.

Moreover, as R_w increases (implying longer residence time of the TC over a given location), d also increases—an effect that is particularly notable in strong TCs. However, the correlation analysis (Figure 2) reveals that the correlation coefficients drop significantly as R_w increases, especially in cases with higher C_d values. Given that R_w in NGR calculations only affects the estimation of d, the decrease in correlation with increasing R_w suggests that this trend is likely due to an overestimation of d. The CD_CN (CD_DC), $R_w = 1R_{max}$ combination, which had the highest correlation coefficient, showed an average mixing depth of 53 m (52 m) and a median of 50 m (50 m). These values align with the findings of Lee et al. (2019), where the 50 m depth-averaged temperature-based NGR demonstrated the highest prediction performance.

3.2 Multi-linear regression model performance

To further quantify the influence of these findings on TC intensity predictions, multi-linear regression models were developed for all combinations, and their skill was evaluated. Following Lee et al. (2019), the predictors included NGR, the previous 12-hour intensity change, and vertical wind shear. The models were trained using data from 2004 to 2017 and evaluated on independent data from 2018 to 2021. We used Principal Component Regression to address multicollinearity, ensuring robust and efficient predictions.

For both tropical storm intensity TCs (≥ TS) and strong TCs (≥ Cat 3), the highest coefficient of determination (R^2) and lowest mean absolute error (MAE) are observed in combinations using $R_w = 1R_{max}$ (Figure 4). Among these, the C_d parameterization with CD_DC consistently demonstrates the best predictive performance, suggesting that $R_w = 1\ R_{max}$ is the most suitable value for capturing the relationship between NGR and 24-hour TC intensity changes. This result aligns closely with the findings from the correlation analysis.

When R_w exceeds 1 R_{max}, both R^2 and MAE degrade for all C_d parameterizations, particularly for strong TCs (≥ Cat 3). This pattern indicates that larger R_w values are less effective in accurately representing the TC-induced mixing. Both R^2 and MAE analyses highlight the poor performance of CD_IC and CD_DN across all R_w values. CD_IC, in particular, shows the lowest R^2 and highest MAE. By comparing the performance of the C_d parameterizations, those that exhibit significant differences above 50 m s^{-1}, the behavior of C_d under extreme wind conditions can be indirectly inferred. The contrasting predictive performance of CD_DC and CD_IC for strong TCs (≥ Cat 3) indirectly suggests that C_d behavior under extreme wind speeds is more consistent with a decreasing trend. This supports the hypothesis that reduced frictional dissipation and suppressed SSC are critical for accurately capturing the dynamics of RI (Kim et al., 2022; Lee et al., 2022). Thus, CD_DC appears better suited for NGR-based TC intensity predictions, as it aligns more closely with the observed physical processes during extreme wind events.

The R^2 and MAE values obtained using the CD_DC are similar to those reported by Lee et al. (2019) when using the 50 m *DAT*-based NGR. In Lee et al. (2019), attempts were made to calculate NGR using SSTs that reflected mixing depths based on TC intensity rather than a fixed-depth average. However, those results did not

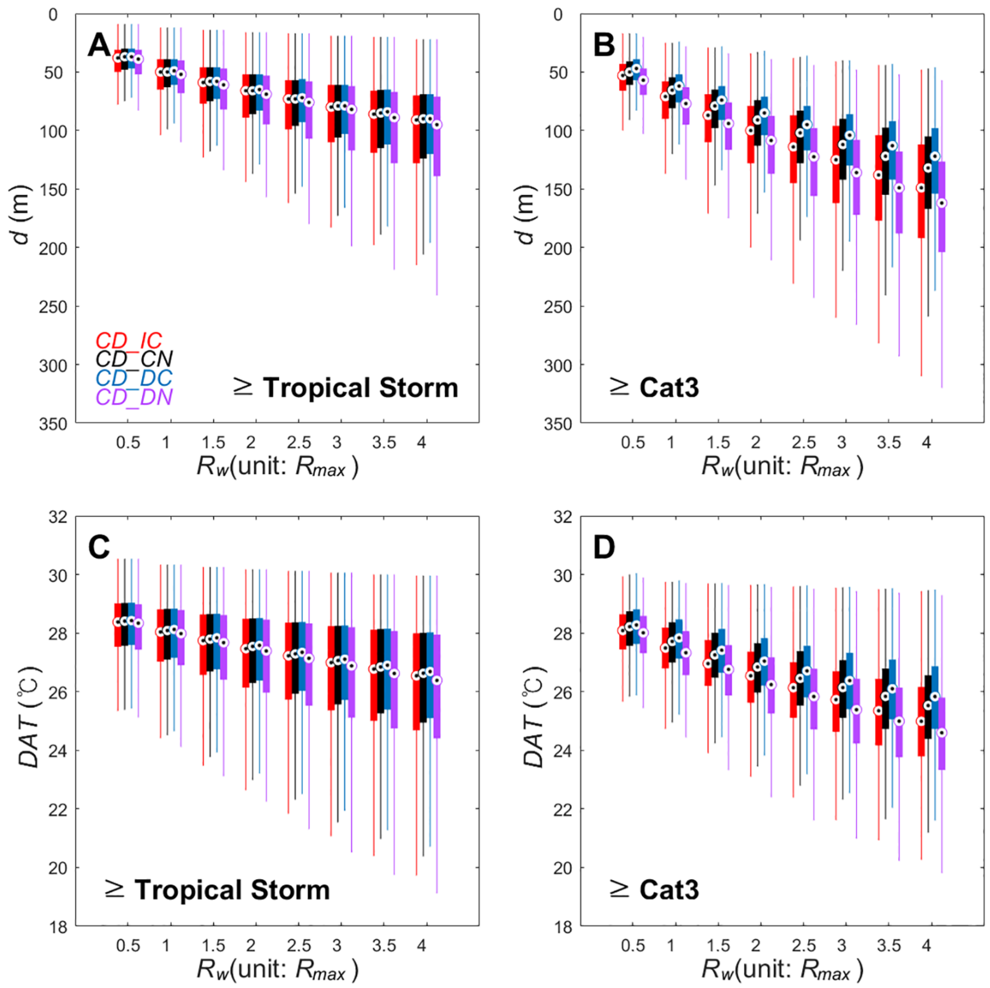

FIGURE 3
Box plot comparison of TC-induced vertical mixing depth (d; upper panels) and the depth-averaged temperature (DAT; bottom panels) as a function of Rw (in units of Rmax) based on different Cd fittings. **(A, C)** Results for TCs at tropical storm intensity or higher (≥ Tropical Storm). **(B, D)** Results for TCs rated at category three or higher on the Saffir-Simpson scale (≥ Cat 3).

outperform the more straightforward 50 m *DAT* approach. Regardless of the C_d parameterization, the d at R_w= $1R_{max}$, which showed the highest correlation coefficient, is around 50–60 m (Figure 3).

However, the regression model combining CD_DC with R_w = $1R_{max}$ shows improved predictive performance compared to the fixed-depth 50 m DAT-based NGR model. Specifically, during the training period (test period), the CD_DC and R_w = $1R_{max}$ model achieved an R^2 of 0.57 (0.54) and MAE of 11.0 (11.8) kt, outperforming the fixed-depth model, which had an R^2 of 0.54 (0.51) and MAE of 11.4 (12.3) kt. These improvements indicate that a more realistic representation of ocean response—calculated by adequately incorporating TC-specific information—can yield higher predictive performance than a uniform 50 m mixing depth. Furthermore, given that the predictive performance of R_w = $4R_{max}$ used before the sensitivity analysis (as evaluated in Lee et al., 2019) was lower than the prediction based on the 50 m DAT, our results demonstrate that carefully tuned sensitivity analyses can significantly improve predictive skill.

4 Summary and discussion

This study conducted a comprehensive sensitivity analysis to investigate the impact of the C_d and the R_w on the NGR and, consequently, on TC intensity changes within 24 hours. By evaluating four different C_d parameterizations—increasing (CD_IC), decreasing (CD_DC), constant (CD_CN), and the control (CD_DN)—and varying R_w from 0.5 to 4 times the R_{max}, we aimed to refine NGR calculations to enhance the predictability of RI events. The results consistently showed that the highest correlations between NGR and observed 24-hour TC intensity changes among all combinations appear at R_w = 1 R_w, particularly for strong TCs (Category 3 or higher). Among the C_d parameterizations, CD_DC —where C_d decreases above 50 m s^{-1}— produces the best predictive performance, followed by CD_CN. This finding aligns with previous studies indicating that a decreasing C_d in extreme winds reduces the negative bias of TC intensity prediction in numerical models (Lee et al., 2022). Furthermore, the analysis of d and DAT revealed that C_d parameterization and R_w values significantly influence upper-ocean

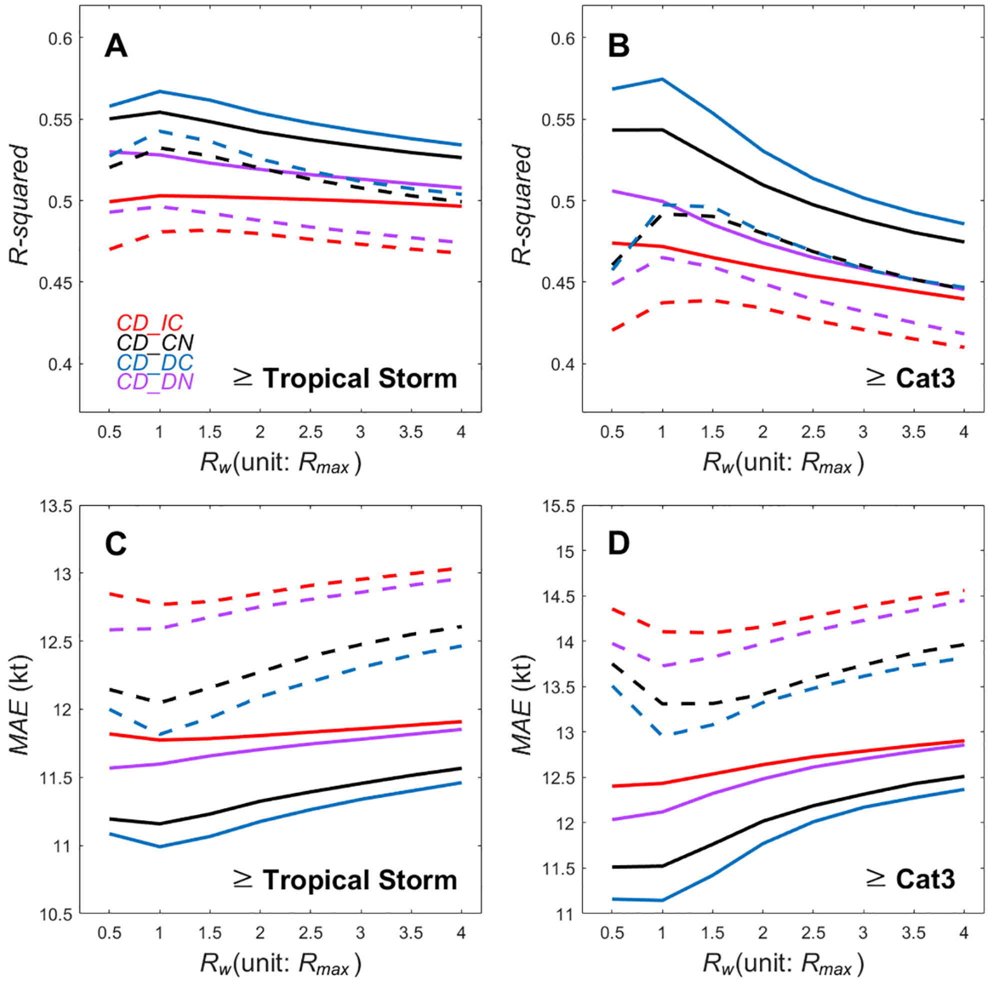

FIGURE 4
Comparison of the R^2 (A, B; upper panels) and the Mean Absolute Error (MAE; C, D; bottom panels) of multi-linear regression models as a function of Rw (in units of Rmax) based on different Cd fittings. **(A, C)** Results for TCs at tropical storm intensity or higher (≥ Tropical Storm). **(B, D)** Results for TCs rated at category three or higher on the Saffir-Simpson scale (≥ Cat 3). Solid lines represent model performance during the training period (2004-2017), while dashed lines represent the results of the test period (2018-2021). The multi-linear regression model incorporates NGR, previous 12-hour intensity change, and 850- to 200-hPa vertical wind shear as predictors, following Lee et al. (2019).

response, which in turn affects TC intensity changes. A lower or constant C_d at high wind speeds, as seen in CD_DC and CD_CN, reduces ocean momentum flux, leading to weaker vertical mixing and higher DAT. This mechanism helps sustain warmer sea surface conditions, which are crucial for TC intensification. While increasing R_w results in a greater d, particularly in strong TCs, the correlation analysis suggests that higher R_w values lead to a decline in correlation coefficients, likely due to d overestimation. The CD_CN (CD_DC) and R_w =1 R_{max} combination exhibited the best correlation and optimal mixing depth (~50 m), aligning with prior studies demonstrating the predictive advantages of a 50 m depth-averaged temperature-based NGR (Lee et al., 2019). In addition, multi-linear regression models that incorporate NGR, previous 12-hour intensity changes, and vertical wind shear were developed to assess predictive performance. The highest R^2 and the lowest MAE are achieved with the combination of CD_DC and R_w = $1R_{max}$, further confirming the findings from the correlation analysis. This consistency between the regression model results and the correlation analysis strengthens the conclusion that the CD_DC and R_w = $1R_{max}$ combination provides the most reliable framework for predicting 24-hour TC intensity changes, particularly for strong TCs experiencing RI events. These findings reinforce the importance of optimizing C_d parameterization and R_w selection to improve TC intensity prediction, particularly for RI events.

Wang et al. (2021) introduced a modified energy-based dynamical system model to explain how the TC intensification rate (IR) varies with storm intensity. According to their findings, the IR depends on the balance between intensification potential (IP) and frictional dissipation, with the IR peaking at an intermediate intensity (30–40 m s^{-1}) before decreasing. A key contribution of their model is the concept of dynamical efficiency, which is governed by inertial stability and clarifies why the IR initially increases but then declines as TC intensifies. The NGR approach focuses on the imbalance between frictional dissipation and enthalpy flux from the sea surface. Kim et al. (2022) demonstrated that the reduction in frictional dissipation within specific intensity ranges where C_d decreases sharply leads to an increase in NGR, which in turn enhances IR in those storm intensity ranges. This aligns closely with the results of Wang et al. (2021), where a large IP relative to frictional dissipation (i.e., high NGR) leads to a higher IR.

Li et al. (2024) found that while a larger size contributes to a higher steady-state intensity, it also reduces the energy conversion efficiency, resulting in two opposing effects that limit the overall impact of size on IR. This study supports the validity of Wang et al. (2021)'s theory and highlights that TC size plays a secondary role in determining intensification rate compared to intensity. However, these results are derived from an atmosphere-only model without considering ocean-atmosphere coupling. TC size significantly influences momentum transfer to the ocean, which in turn affects SSC. Therefore, analyses of TC IR in relation to TC size should consider oceanic feedback to ensure a more comprehensive understanding.

Kim et al. (2022) quantitatively demonstrated that the reduction in C_d for wind speeds exceeding 33 m s^{-1}, using the same parameterization applied in this study, contributes to the increase in NGR through both reduced frictional dissipation and suppressed SSC. Specifically, 75% of the NGR increase was due to reduced frictional dissipation, while 25% was attributed to decreased SSC (DAT increase). This increase in NGR was observed primarily within the TC intensity range (33-50 m s^{-1}), where RI commonly occurs. This finding highlights that C_d reduction plays a dual role in enhancing the available energy for TC intensification, emphasizing both frictional and oceanic thermal effects.

Although the behavior of C_d at wind speeds exceeding 50 m s^{-1} remains uncertain, Kim et al. (2022) demonstrated that a parameterization in which C_d decreases beyond this threshold (i.e., CD_DC) most accurately reproduces the bimodal distribution of lifetime maximum intensity (LMI) in global TCs. Building on this, Lee et al. (2022) introduced an indirect method for estimating C_k/C_d at extreme wind speeds by matching observed LMI with the theoretical MPI. This refined parameterization, which includes a decreasing C_d above 50 m s^{-1}, has been shown to improve intensity forecasts by reducing prediction errors by up to 32% compared to traditional models, highlighting its effectiveness for capturing high-wind dynamics. This result aligns with the findings of Kim et al. (2022), which highlight two key roles of decreasing C_d: reducing frictional dissipation and limiting SSC. These processes contribute to an increase in excess energy, which enhances TC IR. Consequently, this helps mitigate the underestimation of intense TC simulations, a common issue in TC-ocean coupled models.

In this study, we found that applying $R_w = 1R_{max}$ instead of the conventional 4 R_{max} approach reduces the NGR-based TC intensity prediction error by about 10% (Figure 4C; CD_DC, training period). This improvement becomes especially relevant when considering that, during intensification, a TC interacts with an ocean in the midst of an active mixing process rather than one that is already fully homogenized. The traditional assumption of 4 R_{max} implicitly treats the upper ocean as if it were thoroughly mixed by the time the storm passes, which can lead to an overestimation of SSC and subsequently inflate forecast errors in 24-hour intensity change. The roughly 10% reduction in forecast error underscores the importance of selecting an appropriate R_w to avoid overestimating SSC and to better represent the energetics of the storm–ocean system, particularly when RI is likely to occur.

While our study addresses several key uncertainties, notable limitations remain. Yablonsky and Ginis (2009) have shown that the SSC induced by slow-moving TCs (< 5 m s^{-1}) differs substantially between three-dimensional (3D) and one-dimensional (1D) ocean models. Slow-moving TCs induce prolonged mixing and upwelling, resulting in a deeper mixed layer and more significant SST cooling (Tsai et al., 2008; Chu et al., 2020; Yu et al., 2023; John et al., 2024). This suggests that upwelling is crucial in accurately modeling SSC for slow-moving TCs. To assess the impact of TC translation speed on the correlation coefficient of NGR, TCs were divided into two groups: those

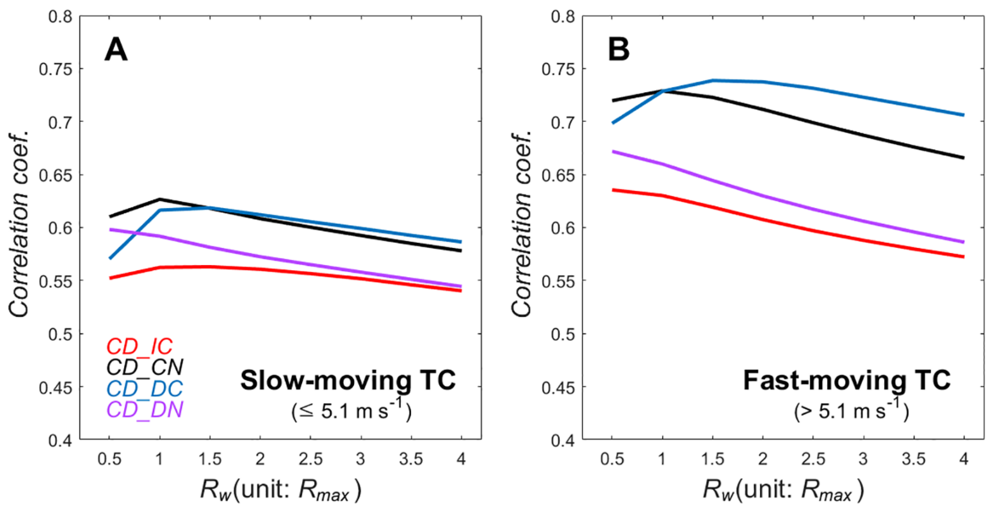

FIGURE 5
Comparison of correlation coefficients between NGR and the 24-hour intensity change based on different C_d fittings as a function of R_w (in units of R_{max}). **(A)** shows results for slow-moving TCs (≤ 5.1 m s^{-1}), and **(B)** represents fast-moving TCs (> 5.1 m s^{-1}). The threshold of 5.1 m s^{-1} corresponds to the median translational speed of analyzed TCs in the western North Pacific.s

with translation speeds ≥ 5.1 m s^{-1} and those with speeds < 5.1 m s^{-1}. The results indicate that the predictive skill of NGR is significantly more excellent for fast-moving TCs (Figure 5). This difference in performance can be attributed to the limitations of the 1D mixing depth estimation model used in this study, which does not account for upwelling. Therefore, to improve the accuracy of NGR calculations for these storms, future work should incorporate a 3D process such as upwelling.

In this study, the C_k was assumed to be a constant in NGR calculations. However, C_d and C_k are crucial in determining TC intensity (Zhang and Emanuel, 2016; Sroka and Emanuel, 2022). The assumption of a constant C_k overlooks the potential impact of wind-speed-dependent changes in enthalpy flux, particularly under extreme wind conditions where sea spray becomes significant (Andreas and Emanuel, 2001; Andreas, 2011). Future studies should investigate the wind-speed dependency of C_k and its interaction with C_d to better represent the energy exchanges during TCs. Collecting more observational data on C_d and C_k under extreme wind conditions is also crucial. Such data would help validate and refine the parameterizations used in predictive models, reducing uncertainties and improving forecast accuracy.

This study underscores the critical importance of accurately parameterizing both the C_d and R_w in modeling the energy exchanges central to TC intensification. By refining these parameters within the NGR framework, we have demonstrated improved predictive skills for RI events. Our sensitivity analyses suggest that a decreasing C_d for wind speeds above 50 m s^{-1}, together with a R_w set to $1R_{max}$, can effectively limit excessive frictional dissipation and sea surface cooling—both of which are essential for maintaining the latent heat flux needed to fuel high-intensity storms. Nevertheless, the scarcity of *in situ* observations under extreme wind conditions highlights the challenges in deriving definitive empirical values for C_d (and possibly C_k). While our results, based on model analysis data, align with the decreasing C_d behavior indicated in prior work (Kim et al., 2022; Lee et al., 2022), we acknowledge that deeper insight into TC-induced ocean mixing requires additional observational validation. For instance, Argo float measurements collected during a storm's passage could directly estimate the mixing depth, enabling more precise momentum-transfer calculations. Incorporating such real-time observational data is inherently difficult—especially in an operational forecasting context—but remains a vital goal for future research. Finally, our findings highlight the need for further improving the realism of TC-ocean coupled models, particularly by incorporating three-dimensional ocean processes and wind-speed-dependent changes in both C_d and C_k. Such enhancements would help mitigate the systematic underestimation of intense TCs and strengthen the reliability of intensity forecasts. Continued investigations in this domain are crucial not only for advancing the scientific understanding of TC dynamics but also for reducing the societal impacts of these devastating phenomena through more accurate prediction and preparedness.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

SK: Conceptualization, Formal Analysis, Investigation, Writing – original draft, Writing – review & editing, Methodology. WL: Data curation, Methodology, Writing – review & editing, Formal Analysis. SW: Data curation, Methodology, Validation, Writing – review & editing. H-WK: Supervision, Validation, Writing – review & editing. KK: Project administration, Validation, Writing – review & editing. SK: Conceptualization, Supervision, Validation, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was supported by Korea Institute of Marine Science &Technology Promotion (KIMST) funded by the Ministry of Oceans and Fisheries (20220566). This research was supported by the project titled "Development of typhoon analysis and forecast technology (KMA2018-00722)" of the National Typhoon Center at the Korea Meteorological Administration.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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