

Performance evaluation of COAWST model in simulating typhoon “Soulik” on Kunpeng (ARM) and Intel (x86) architectures*

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Abstract High-resolution Earth system models are essential for understanding and predicting extreme weather events. However, the performance of complex coupled models on ARM architectures and the intrinsic uncertainties introduced by the underlying computing infrastructure remain inadequately assessed in quantitative geophysical simulations. Using Typhoon Soulik (2013) as a case, this work ports the Coupled Ocean-Atmosphere-Wave-Sediment Transport (COAWST) model to a Huawei Kunpeng (ARM) server and systematically evaluates its performance and physical consistency against an Intel (x86) server, which was then validated with multi-source observational data. Results show that the ARM-based simulation reduced computational time by 15.44%. Both platforms achieved high consistency in simulating typhoon evolution and oceanic response ($R^2 > 0.99$), confirming the reliability of ARM for scientific modeling. Quantitative analysis further revealed discernible architectural influences: dynamical errors exhibited spatiotemporal clustering, and the ARM platform showed slightly weaker air-sea coupling during landfall but better performance in simulating near-surface wind speed (0.23% reduction in RMSE). These findings highlight computing architecture as a source of uncertainty in high-resolution simulations and underscore the need for cross-platform validation in future research. This study verified the efficiency and stability of the ARM architecture for high-resolution coupled modeling and offered a reliable pathway for advancing ocean and extreme weather research through diversified high-performance computing infrastructure.

Keyword: COAWST model; Kunpeng 920; tropical cyclone; high-performance computing; ARM architecture; model validation

1 INTRODUCTION

High-performance computing (HPC) has become an indispensable tool in modern science and engineering, driven by the continuous evolution of computing architectures. Over the past decade, x86 architecture processors have dominated the HPC landscape due to their robust computational performance and mature software ecosystem (Zhang et al., 2024).

According to the November 2024 TOP500 supercomputer rankings, over 95% of supercomputing platforms rely on x86 processors, with the top five systems, including the El Capitan supercomputer

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powered by AMD's 4th-generation EPYC processors, achieving an HPL score of 1.742 EFlop/s. This dominance highlights the entrenched position of x86 processors in HPC. However, as Moore's Law slows (Thompson and Parthasarathy, 2006), advancements in transistor technology for x86 architectures have plateaued, diminishing marginal performance gains. Simultaneously, the escalating computational demands of HPC, particularly for exascale computing (10^{18} FLOPS), present significant challenges in scalability, power consumption, and thermal management (Geist and Reed, 2017). In this context, ARM architectures have emerged as a promising alternative in the HPC market, owing to their low power consumption, high energy efficiency (performance per watt), and well-designed reduced instruction set computing (RISC) architecture (Senger et al., 2019).

Originally being developed for mobile and embedded systems, ARM processors have recently expanded into server-grade applications, prompting major enterprises to develop ARM-based solutions for HPC (Rico et al., 2017; Gwennap, 2018; Sorensen, 2019). The RISC design of ARM processors facilitates large-scale parallel computing, offering superior energy efficiency compared to x86 counterparts. A landmark achievement in ARM-based HPC was the deployment of Japan's Fugaku supercomputer, developed by RIKEN in 2020, which, powered by the ARM-based A64FX processor, not only led global performance benchmarks (Langarita et al., 2023) but also demonstrated high-fidelity climate simulations (Yashiro et al., 2021). Additionally, server-grade ARM processors, such as Huawei's Kunpeng 920, have broadened ARM's applicability to data centers and HPC, showcasing their potential for complex scientific computations (Xia et al., 2021).

Among those mentioned above, Huawei's Kunpeng 920 processor represents a significant advancement in the ARM server ecosystem. Designed specifically for HPC and data center workloads, it distinguishes itself through a high-core-count architecture and a full-stack, co-designed software environment. Its key features, which include a scalable multi-core design, high memory bandwidth, and an integrated software suite comprising the Bisheng Compiler, Kunpeng Math Library, and Hyper Message Passing Interface, are engineered to address modern HPC challenges in scalability and energy efficiency. This integrated design positions it as an ideal candidate for large-

scale oceanographic and meteorological simulations (Huang et al., 2023).

The rapid proliferation of ARM-based HPC platforms has spurred the evaluation of computationally intensive models on these architectures. While ARM-based platforms may offer energy-efficiency advantages, maintaining numerical consistency is particularly important for complex coupled systems such as the Coupled Ocean-Atmosphere-Wave-Sediment Transport (COAWST) model. COAWST has been extensively applied in regional climate change investigations (Jiang et al., 2025), extreme weather and storm surge studies (Shi et al., 2019; Leung et al., 2024), and sediment transport research (Zhang et al., 2021). However, its computational complexity and large data requirements necessitate substantial HPC resources, particularly at high-resolution settings. For example, simulating Typhoon Sandy (2012) with a parent domain of 87×65 grid points (approximately $20\text{-km} \times 26\text{-km}$ resolution), a nested domain of 116×86 grid points (approximately $6\text{-km} \times 9\text{-km}$ resolution), a 15-s time step, and 11 520 time steps over a 2-d period required over 6 000 s of computation time on three cores, even on x86-based platforms (Zang et al., 2018).

Despite its widespread use on x86-based HPC systems, systematic performance evaluations of COAWST on ARM architectures remain limited. Therefore, this study ports and optimizes the COAWST model on a Kunpeng high-performance computing platform, conducting rigorous comparative experiments against an x86 system for Typhoon Soulik, integrated with multi-source observational data. This study aims to achieve two primary objectives: to systematically evaluate the computational efficiency and scientific robustness of the ARM platform for coupled ocean-atmosphere modeling, and to quantitatively characterize the magnitude and spatiotemporal distribution of simulation uncertainties attributable to architectural differences.

2 KUNPENG 920 PROCESSOR AND SOFTWARE ECOSYSTEM

The Kunpeng 920 processor is a high-performance and server-grade processor independently developed by Huawei based on the ARM architecture, primarily targeting HPC and data center applications. Compatible with the ARMv8.2 architecture, it supports a 64-core design with a base frequency of up to 2.6 GHz and integrates I/O chips to provide robust parallel computing capabilities. With

advanced memory control and management, the Kunpeng 920 supports 8-channel DDR4 memory with a maximum bandwidth of 2 933 MT/s, ensuring efficient data transfer for high-performance computing tasks. The processor adopts a Non-Uniform Memory Access (NUMA) architecture, optimizing memory access efficiency in multi-core systems, reducing latency, and improving scalability. In the NUMA architecture, multiple cores are grouped into nodes that communicate via an on-chip network, while different CPUs are interconnected using Hydra Interface technology. This design facilitates high-speed communication both within and between chips, significantly reducing latency and making it well-suited for compute-intensive tasks.

The Kunpeng HPC platform offers a compelling hardware proposition through its multi-core Kunpeng 920 processors, which are based on an efficient ARM RISC architecture, ensuring high performance and cost-effectiveness. To develop this hardware potential, the Kunpeng HPC establishes a comprehensive software ecosystem, featuring the deeply optimized Bisheng Compiler, the Kunpeng Math Library (KML), and the Hyper Message Passing Interface (HMPI). Together, this integrated full-stack environment was designed to meet the demanding requirements of large-scale parallel applications such as the COAWST model. The capabilities of Kunpeng HPC have been validated in multiple HPC projects. For instance, in the tests of the Weather Research and Forecasting (WRF) model, Kunpeng HPC platforms demonstrated superior energy efficiency and scalability, confirming their potential in scientific computing (Chen et al., 2024). To further evaluate the performance of Kunpeng HPC platform in oceanographic and meteorological modeling and to quantify the impact

of the computing architecture on the simulation of hurricane structure and ocean response, we compared the COAWST simulation results, optimized and ported them to Kunpeng HPC (ARM-based) with those obtained from Intel HPC (x86-based) and independent observational data. The test experiments utilized Kunpeng HPC with each server equipped with two Kunpeng 920-7260 processors, and Intel HPC with two Intel Xeon Gold 6240R processors. Each Kunpeng 920 processor features 64 physical cores, a base frequency of 2.60 GHz, and 64MB of shared L3 cache, totaling 128 physical cores per server, configured as a dual-NUMA node system. Each Intel Xeon Gold 6240R processor features 24 physical cores, a base frequency of 2.40 GHz, and 35.75 MB of shared L3 cache, totaling 48 physical cores per server, also configured as a dual-NUMA node system. The configurations of both computing platforms are comparable, as detailed in Table 1. The network topology used for testing is a standard fat-tree network, meeting the low-latency, high-throughput requirements of HPC projects. The COAWST model on both platforms is initialized with the same initial conditions, parameter settings, and boundary conditions (see Section 3.2 for detail), and observational data sources are described in Section 3.3.

3 MODEL AND METHOD

This section briefly introduces the COAWST model, the selected case for performance evaluation, optimizations of COAWST on Kunpeng HPC, and the analysis methodology.

3.1 COAWST model

The COAWST model is a modular coupled modeling system composed of multiple Fortran

Table 1 The test environment configuration for Kunpeng and Intel HPC

Item	Kunpeng HPC	Intel HPC
Cluster	Huawei Atlas 900	Sugon
Architecture	Armv8.2	x86_64
Processor	2×Kunpeng 920-7260 (64C, 2.6 GHz)	2×Xeon Gold 6240R (24C, 2.4 GHz)
Memory	Hynix DDR4, 2933 MHz	DDR4, 2933 MHz
Storage	Local: 2×300 GB SAS Shared: OceanStor Pacific (10 TB)	Local: 1×600 GB SAS Shared: OceanStor Pacific (10 TB)
Network	Management: GE Interconnect: Mellanox ConnectX-5 (dual-port)	Management: GE Interconnect: Mellanox ConnectX-5 (dual-port)
OS	CentOS 7.6	CentOS 7.6
Compiler	Bisheng 2.1.0	Intel OneAPI 2021.1.0
MPI	HyperMPI 1.1.1	Intel OneAPI 2021.1.0
Math library	KML 1.4.0	Intel OneAPI 2021.1.0

files, configuration scripts, and data interface files. COAWST enhances environmental simulation accuracy by incorporating inter-module interactions (Warner et al., 2010). The system is highly flexible, allowing users to define key parameters such as resolution, boundary conditions, and initial conditions by modifying configuration files. The model supports MPI-based distributed parallel computing, efficiently utilizing multi-core and multi-node resources. The classical COAWST model consists of several components: the Regional Ocean Modeling System (ROMS) (Shchepetkin and McWilliams, 2005) for simulating oceanic dynamical processes, the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008) for high-resolution atmospheric dynamics simulations, the WAVEWATCH III (WW3) model (Tolman, 1991) for generating and propagating nearshore waves, and the sediment component (Warner et al., 2008) for studying sediment erosion, deposition, and transport processes. These components are coupled using the Model Coupling Toolkit (MCT) (Larson et al., 2005), which synchronizes time steps and exchanges physical variables among the modules, ensuring stability and accuracy of the coupled system. This coupling enables critical interactions, for instance, the wave component provides data on wave-induced mixing to the ocean model, which is essential for realistically simulating upper ocean thermal structure and mixed layer depths (Dai et al., 2010; Shu et al., 2011).

3.2 Model configuration

This study employs the COAWST modeling system, integrating WRF, WW3, and ROMS to simulate high-fidelity interactions among the atmosphere, waves, and ocean circulation. The selected case study focuses on Typhoon Soulik, which formed over the northwestern Pacific Ocean in July 2013, traversed Taiwan, China, and made landfall in Fujian Province, China, on July 13. The simulation period spans from 00:00 UTC on July 10 to 00:00 UTC on July 15, 2013. The spatial domain for all three model components (atmosphere, ocean, and waves) covers the region from 28.16°E to 177.83°E and from 28.57°S to 41.65°N, discretized into a horizontal grid of 750×380 cells, yielding an approximate resolution of 22 km.

For the ROMS component, 30 vertical layers are configured, with a time step of 30 s. The model employs a third-order upstream horizontal advection scheme and a fourth-order centered vertical

advection scheme. Boundary conditions include Chapman for free-surface perturbation, Flather for depth-averaged currents, and radiation with nudging for other variables. Vertical mixing is parameterized using the Generic Length Scale (GLS) k - ϵ turbulence closure model, with tidal forcing enabled. Initial and boundary conditions for ocean fields such as currents, depth-averaged currents, sea level, salinity, and temperature are derived from the global HYCOM reanalysis (available at <http://hycom.coaps.fsu.edu/thredds/catalog.html>), which has a spatial resolution of 1/12° and provides output at 3-hourly intervals. Tidal forcing at the lateral open boundaries is provided by the TPX09-atlas (Egbert and Erofeeva, 2002), incorporating eight tidal constituents (Q_1 , O_1 , P_1 , K_1 , N_2 , M_2 , S_2 , and K_2) on a 1/30° grid.

The WRF component is configured as a single domain with 48 vertical levels and a time step of 60 s. Physical parameterizations include the WSM6 microphysics scheme, Kain-Fritsch cumulus parameterization, RRTM longwave radiation, Dudhia shortwave radiation, YSU planetary boundary layer scheme, and Noah land surface model. Initial and boundary conditions are obtained from the NCEP Final Analysis Global Forecast System (GFS) data (available at <http://dss.ucar.edu/datasets/ds083.2/>), which has a spatial resolution of 1° and a temporal resolution of 6 h. To better capture the typhoon dynamics, the initial wind fields (U_{wind} , V_{wind}) and sea level pressure (PMSL) are locally scaled based on GFS data and observed typhoon conditions. Sea surface temperature (SST) boundary conditions are updated daily using the NCEP Real-Time Global (RTG) SST analysis (Gemmell et al., 2007; <ftp://polar.ncep.noaa.gov/pub/history/sst/>), which features a spatial resolution of 0.083°.

The WW3 component runs synchronously with WRF, receiving input fields such as wind, sea level, and ocean currents, and providing outputs of mean wave parameters and point-specific wave data. For coupling control, WRF, WW3, and ROMS are allocated 36, 12, and 36 MPI processes respectively, with a coupling interval of 3 600 s. Data interpolation between different model grids is performed using the Spherical Coordinate Remapping and Interpolation Package (SCRIP) (Jones, 1999), which generates interpolation weights stored in a single NetCDF weight file, ensuring efficient and accurate data exchange among the components. This configuration, with its detailed parameterizations and robust coupling mechanisms, provides a reliable scientific

tool for investigating the impacts of extreme weather events on the marine environment (Fig.1).

3.3 Optimization of COAWST on the ARM-Based HPC

The multi-module collaborative nature of COAWST enables the simulation of complex interactions among the atmosphere, ocean, and waves but also significantly increases computational costs, imposing higher demands on computational resources and efficiency. To fully utilize the advantages of Kunpeng HPC, which is based on the ARM architecture, this study optimized COAWST by addressing communication algorithm efficiency, compiler performance tuning, memory management, matrix computation acceleration, and parallel I/O performance enhancements. These optimizations not only improved computational performance but also reduced energy consumption, ensuring the model's stability and efficiency in large-scale parallel computing.

Given that COAWST's large-scale parallel execution relies heavily on efficient inter-process data exchange, Kunpeng HPC employs the HMPI communication library and optimizes load balancing mechanisms. HMPI specifically enhances global reduction operations (Allreduce) and leverages the multi-channel memory advantage of Kunpeng processors, distributing MPI ranks evenly across different NUMA nodes. This fully utilizes the memory bandwidth and capacity of 64 core nodes, improving communication performance by approximately 10% compared to Intel MPI and

enhancing overall system efficiency. Additionally, COAWST contains numerous memory operation hotspots (e.g., malloc and memcpy), which were deeply customized using the Bisheng compiler. The integration of the jemalloc memory allocation library significantly improved memory management efficiency, leading to about a 20% increase in computational speed, particularly in the ROMS model.

To further accelerate core computational tasks, the optimized KML improved matrix computation and numerical integration performance. Specific optimizations to the frequently used reshape function enhanced compiler auto-vectorization capabilities, boosting matrix operation performance by approximately 10%. Regarding data I/O, given that COAWST's NetCDF input/output files often exceed 800 GB, the ARM platform adopted ParallelIO (PIO) technology, significantly reducing data access time through multi-process parallel read/write operations and improving data throughput efficiency in high-resolution simulations. Kunpeng HPC employs Huawei's HCCS interconnect protocol, supporting up to four-way interconnects, enhancing multi-core scalability and providing hardware support for COAWST's multi-module collaborative computing. The core model of COAWST (WRF, ROMS, WW3) have active communities and development teams, offering extensive online documentation and user support, ensuring the ease of model configuration and optimization. These optimizations have gained community attention, laying a foundation for the promotion of Kunpeng HPC in scientific computing.

3.4 Evaluation method

To evaluate the reliability of COAWST simulation results after porting to Kunpeng servers and to quantitatively analyze differences between the ARM-based (Huawei Atlas 900 cluster) and x86-based (Sugon cluster) servers, numerical simulation experiments were conducted on both platforms and cross-validated with independent observations. This paper abbreviates the COAWST implementation on the Huawei Atlas 900 cluster as "COAWST(ARM)" and that on the Sugon cluster as "COAWST(x86)". The track, intensity, and strength of tropical cyclones, SST, sea surface stress, sea surface height (defined as instantaneous sea level displacement relative to the static still-water datum), surface current velocity, and significant wave height are not only critical indicators of ocean-atmosphere-wave dynamics and thermodynamics but also directly

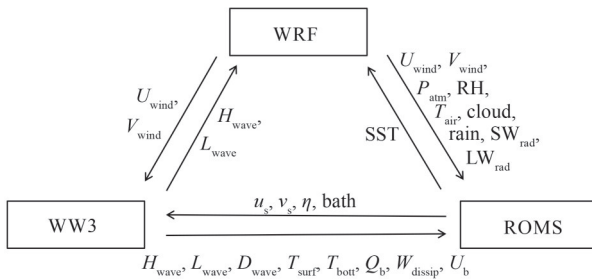


Fig.1 Physical variables exchanged in COAWST

U_{wind} and V_{wind} : zonal and meridional 10-m wind velocity components; P_{atm} : sea level atmospheric pressure; RH : relative humidity; T_{air} : near-surface air temperature; $cloud$: cloud fraction; $rain$: precipitation; SW_{rad} and LW_{rad} : downward shortwave and longwave radiation; SST : sea surface temperature; u_s and v_s : surface horizontal current velocity components; η : free surface elevation; $bath$: bathymetry; H_{wave} : significant wave height; L_{wave} : mean wavelength; D_{wave} : mean wave direction; T_{surf} and T_{bot} : mean surface and bottom wave periods; Q_b : fractional wave breaking; W_{dissip} : total wave energy dissipation; U_b : near-bottom wave orbital velocity.

influence the coupled model outputs through air-sea interactions and wave-current coupling, and other dynamic processes. Therefore, cross-comparing model output variables on ARM (Huawei Atlas 900 cluster) and x86 (Sugon cluster) platforms with satellite remote sensing reanalysis products and station observations not only allows for a comprehensive assessment of the impact of hardware architecture on numerical simulation accuracy but also provides deeper insight into the spatial and temporal distribution and propagation of errors in the coupled system.

The best track data for Typhoon Soulik, including the storm's center position and intensity (maximum sustained winds and minimum central pressure), was obtained from the Historical Typhoon Information database of the National Institute of Informatics, Japan (<https://agora.ex.nii.ac.jp/digital-typhoon/summary/wnp/1/201307.html.ja>). The data is provided at 3-h intervals from 00:00 UTC July 11 to 00:00 UTC July 13, and at 6-h intervals for other periods during the event. Hourly marine meteorological data from observational stations were sourced from the ocean station observation dataset of the National Marine Data and Information

Service (NMDIS, China; <https://mds.nmdis.org.cn>) and from the Climate and Ocean Data Information System (CODIS) of the Central Weather Administration (CWA) in Taiwan, China (<https://codis.cwa.gov.tw/StationData>). The station locations are shown in Fig.2. For broader-scale validation, gridded SST data were obtained from the hourly ERA5 reanalysis (Hersbach et al., 2020; <https://cds.climate.copernicus.eu/datasets>), which has a spatial resolution of $0.25^\circ \times 0.25^\circ$ (approximately 28 km). Sea level anomaly (SLA) data were derived from the daily gridded AVISO satellite altimetry product, which also features a spatial resolution of $0.25^\circ \times 0.25^\circ$ (<https://www.aviso.altimetry.fr>). It is important to note that while both datasets incorporate satellite measurements, they represent different product categories: ERA5 is a model-based reanalysis that assimilates various observations, whereas AVISO provides gridded sea level anomaly estimates derived from multi-mission satellite altimetry.

This paper focuses on the primary impact zone of Typhoon Soulik (2013). A comprehensive validation was conducted for the analysis domain (16°N – 32°N , 110°E – 155°E) using multiple statistical metrics: mean error (ME), mean absolute error (MAE), root mean

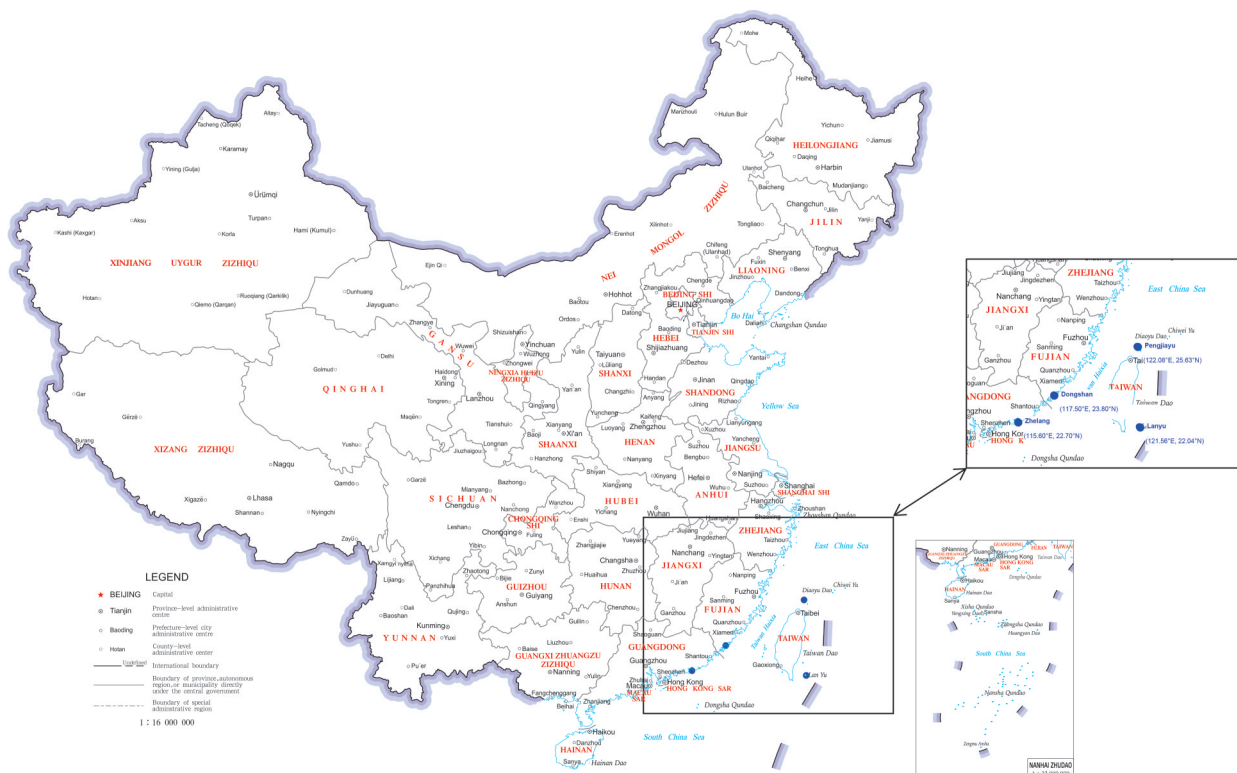


Fig.2 Station locations in the coasts of SE China continent and Taiwan Island, China

The stations from north to south with their coordinates: Pengjiayu (122.08°E , 25.63°N), Dongshan (117.50°E , 23.80°N), Zhelang (115.60°E , 22.70°N), Lanyu (121.56°E , 22.04°N). Map review number: GS(2019)1686.

square error (RMSE), and coefficient of determination (R^2), with both temporal and spatial evaluations implemented. Taking RMSE as an example, the spatio-temporal calculation is described as Eqs.1 & 2,

$$\text{RMSE}_{\text{time}}(t) = \sqrt{\frac{\sum_{i=1}^n (S_i(t) - O_i(t))^2}{n}}, \quad (1)$$

where $O_i(t)$ is the observed value at time t at grid point i , $S_i(t)$ is the corresponding simulated value, and n is the total number of grid points in the analysis region.

$$\text{RMSE}_{\text{point}}(i) = \sqrt{\frac{\sum_{t=1}^m (S_i(t) - O_i(i))^2}{m}}, \quad (2)$$

where $O_i(i)$ is the observed value at grid point i at time t , $S_i(i)$ is the corresponding simulated value, and m is the total number of time steps in the observational dataset.

Since model grid points do not perfectly align with observation stations or remote sensing grid points, the radial basis function (RBF) interpolation method was used to obtain simulated values at observational locations. The RBF method is widely used in various applications (Franke, 1982; Vennell and Beatson, 2006) and has relatively high interpolation accuracy for discrete data (Rocha, 2009). Given the simulation results recorded as (x_i, y_i) , $i=1, 2, \dots, n$, representing the coordinates of grid point i projected using the Miller projection, the interpolated simulation value at a specific location (x_j, y_j) can be computed as Eq.3:

$$f_j = \sum_{i=1}^n \alpha_i \cdot \phi(d_{ij}), \quad (3)$$

where d_{ij} is the Euclidean norm between coordinates (x_i, y_i) and (x_j, y_j) , $\phi(d_{ij})$ is the basis function, and α_i ($i=1, 2, \dots, n$) are constants solved using the least squares method. The three RBF interpolation functions employed in this study are:

$$\phi(d_{ij}) = d_{ij}, \quad (4)$$

$$\phi(d_{ij}) = d_{ij}^3, \quad (5)$$

$$\phi(d_{ij}) = e^{-\frac{d_{ij}^2}{2\varepsilon^2}}, \quad (6)$$

i.e., (1) linear (Eq.4), (2) cubic (Eq.5), and (3) Gaussian (Eq.6), where the constant ε is the inverse of the critical radius, set to $\varepsilon=0.1$ in this study.

For station interpolation, the RBF method with the smallest RMSE against observations is selected. Since the differences between results from the three RBF methods were minimal, the linear RBF interpolation method was generally used for interpolating simulation results at remote sensing grid points to save computational cost.

4 RESULT AND DISCUSSION

The COAWST model was used in this study to simulate Typhoon Soulik (2013) on the Huawei Atlas 900 cluster (ARM architecture) and the Sugon cluster (x86 architecture). The simulation spanned from 00:00 UTC on July 10 to 00:00 UTC on July 15, with a coupling time step of 3 600 s and 84 MPI processes. The total computation time was 15 510.73 s on the ARM system (2 CPUs) and 18 342.06 s on the x86 system (2 CPUs with hyper-threading enabled), indicating an approximately 15.44% parallel efficiency advantage for the ARM architecture. The performance gain could be mainly attributed to two factors. First, the Kunpeng platform fully leveraged its abundant physical cores to effectively avoid process oversubscription and hardware resource contention. Second, the ARM architecture delivered superior memory bandwidth adaptability for this memory-intensive COAWST coupled model. To evaluate the reliability of the numerical simulations, model outputs were systematically compared with multiple independent datasets, including satellite remote sensing and station observations, with a focus on how different hardware architectures influence the simulation of coupled storm surge physical fields.

4.1 Accuracy assessment of simulated typhoon dynamics

To investigate whether computing architecture differences could lead to deviations in simulated typhoon tracks, we compared the simulated track and intensity evolution of Typhoon Soulik from July 10 to July 14, 2013 (UTC), as produced by the COAWST model on both platforms, with historical best-track observations (Fig.3). According to observational data, Soulik formed over the western Pacific at 145.4°E, 18.9°N on July 8, peaked on July 10 (925 hPa, 51.44 m/s), and then turned northwestward while gradually weakening. On July 12, Soulik passed over northern Taiwan, China, where terrain-induced forcing enhanced low-level convergence and upper-level divergence, and the resulting secondary circulation led to a brief intensification,

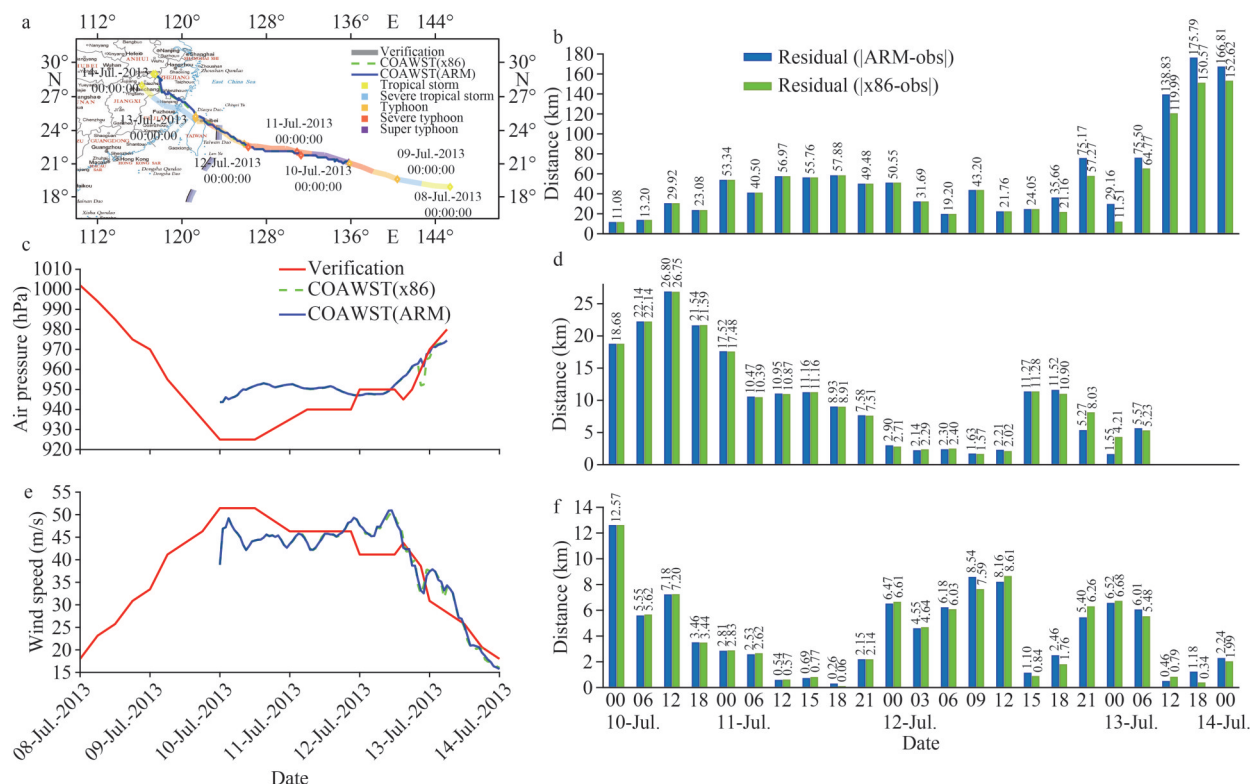


Fig.3 Comparison of simulated and observed typhoon track and intensity

Left panels (a, c, e). simulated results from COAWST(ARM) (blue solid lines) and COAWST(x86) (green dashed lines) against best-track observations (observed track as color-coded fluorescent line in (a); observed intensity as red solid lines in (c, e)); right panels (b, d, f). residuals of COAWST(ARM) (blue bars) and COAWST(x86) (green bars) relative to observations for track, maximum wind speed, and minimum central pressure, respectively.

with observed pressure dropping 5 hPa and wind speed increasing 2.57 m/s, before landfall in southeastern China and rapid dissipation due to surface friction.

The COAWST simulation was initialized on July 10 when the typhoon was near peak intensity. But due to the underestimation of its initial intensity in the model, the simulated track lagged observations during the early and mid-stages, with a maximum track error of approximately 75 km and a southeastward bias. In the later stages, the track shifted slightly northeastward. Both platforms produced nearly identical tracks up to 15:00 on July 12, but after 18:00, COAWST(ARM) shifted further north compared to COAWST(x86), resulting in a 1-h delay in landfall over Taiwan Island, China (22:00 vs. 21:00). Both simulations captured the terrain-induced temporary intensification, with COAWST(x86) showing a slightly stronger response (pressure drop of 10.92 hPa, wind speed increase of 5.90 m/s) compared to COAWST(ARM) (pressure drop of 3.64 hPa, wind speed increase of 5.32 m/s) and to the observations.

Overall, the COAWST model on both platforms

effectively reproduced Soulik's track and intensity variations. RMSE comparisons against historical observations showed that COAWST(x86) had slightly lower track error (by 1.58 km), whereas COAWST(ARM) better simulated central pressure (by 0.012 hPa), with differences in maximum wind speed on the order of 10^{-3} . Track errors were primarily concentrated around the landfall period, likely associated with accumulated uncertainties in pressure gradient and wind field reconstruction within the high-wind zone. Despite 24-h climatological corrections, late-stage track errors increased on both platforms, reflecting the chaotic nature of typhoon dynamics and its sensitivity to minute numerical discrepancies. The divergence between the COAWST(ARM) and COAWST(x86) tracks after July 12 18:00 likely stemmed from the amplification of architecture differences in the model running. These included subtle variations in floating-point rounding from the Bisheng and Intel compilers, and differences in the order of operations within the dynamical solvers of WRF and ROMS. Over time, these small perturbations in calculating pressure gradients and wind fields within the high-wind zone

grew non-linearly, leading to the observed spatial deviation. This demonstrates that even with identical model physics and configuration, the computing architecture itself introduces a quantifiable pathway for uncertainty in long-term simulations.

4.2 Evaluation of coastal atmospheric variable simulations

To further assess the simulation accuracy of the COAWST model across different platforms, meteorological variables, including surface pressure (SP), wind speed, and SST, were compared against station observations at selected southeastern coastal sites (see Fig.2; results in Fig.4). The model initially underestimated SP at most stations, and the simulated pressure remained generally lower outside

of periods strongly influenced by the typhoon. Wind speed, on the other hand, tended to be overestimated at some coastal stations, especially following landfall.

While the overall trends agreed well with observations, platform-specific discrepancies emerged from July 12 onward, with the wind speed residual fluctuations exhibiting no constant trend. During periods of strong pressure gradients, the COAWST (x86) simulation aligned better with observations at Zhelang station, whereas COAWST(ARM) performed more accurately at Dongshan station. Over the full simulation period, COAWST(ARM) achieved lower RMSEs in SP at both stations (1.240 1 hPa at Zhelang, 3.334 6 hPa at Dongshan), as well as in wind speed (1.689 5, 2.745 9 m/s), respectively (Table 2).

At the Pengjiayu station east of Taiwan, China,

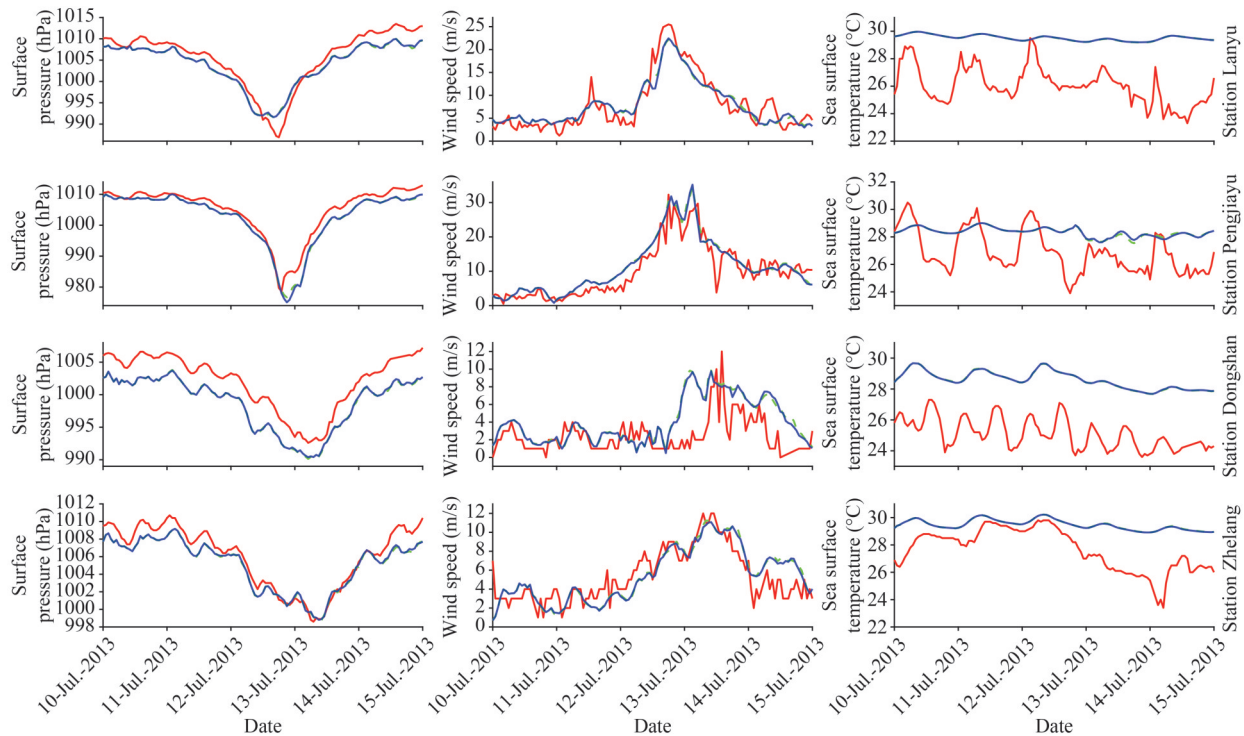


Fig.4 Comparison of surface pressure, wind speed, and sea surface temperature between COAWST simulations on two computing platforms and station observations

COAWST(ARM) results are shown as blue solid lines, COAWST(x86) as green dashed lines, and observational data as red solid lines.

Table 2 Root mean square errors (RMSEs) of COAWST simulations at selected stations compared to the observations

Station	Surface pressure (hPa)		Wind speed (m/s)		Sea surface temperature (°C)	
	RMSE (ARM & obs)	RMSE (x86 & obs)	RMSE (ARM & obs)	RMSE (x86 & obs)	RMSE (ARM & obs)	RMSE (x86 & obs)
Lanyu	2.421 1	2.448 3	2.430 1	2.346 3	3.707 4	3.702 5
Pengjiayu	2.877 7	2.768 7	3.234 5	3.251 5	2.076 1	2.064 1
Dongshan	3.334 6	3.384 7	2.745 9	2.796 5	3.593 6	3.590 9
Zhelang	1.240 1	1.269 1	1.689 5	1.733 8	2.223 3	2.232 7

“ARM” refers to COAWST(ARM) simulation results, “x86” COAWST(x86), and “obs” observational data.

which is located closer to the COAWST (ARM) simulated track, SP minima were slightly underestimated and wind speed peaks appeared sharper. At Lanyu station, COAWST(ARM) yielded better agreement with observed SP (RMSE=2.421 1 hPa), indicating its higher sensitivity in capturing typhoon structure. Although the timing of SP minima at each station slightly deviated from observations, likely due to the northward bias in simulated typhoon tracks, temporal alignment between the two platforms remained consistent and within acceptable error bounds.

SP and wind speed errors were most prominent near Taiwan, China, particularly around landfall, and were closely associated with spatial deviations in the simulated typhoon track. COAWST(ARM) showed more stable and lower errors at stations farther from the typhoon center, generally outperforming COAWST(x86) in terms of fit. Regional RMSE in SP was 0.143 3 hPa (correlation coefficient: 0.999 9), and in wind speed 0.327 3 m/s (correlation coefficient: 0.993 7), indicating high consistency between the two platforms. COAWST (ARM) achieved lower SP RMSEs at most stations compared to COAWST(x86), with wind speed RMSE decreased by 0.23%, suggesting a slight performance advantage of the WRF module on the ARM-based Kunpeng HPC.

Except at Pengjiayu, SST was consistently overestimated from the beginning of the simulation, likely due to warmer initial conditions set near the continental margin. SST values remained higher than observations throughout the period, with smoother variability. At Pengjiayu, both models reasonably captured typhoon-induced cooling due to turbulent mixing, with mean SST bias around 0.05 °C. A shift occurred after 22:00 on July 13, before which COAWST(ARM) produced higher SST, while COAWST(x86) became warmer thereafter. This reflects subtle differences in the simulation of SST responses to upwelling, mixed-layer deepening, and solar radiation between the platforms.

At other stations, results also suggest that floating-point precision and numerical treatment on ARM and x86 platforms may lead to cumulative differences in small-scale mixing over time. These cumulative differences may arise from architectural disparities. The Kunpeng 920 processor, with its high core count and optimized memory controller, may handle the intense, irregular memory access patterns of the planetary boundary layer scheme differently than the Intel Xeon processors.

Furthermore, the Bisheng compiler's vectorization of the YSU scheme loops could lead to a different sequence of floating-point operations compared to the Intel compiler. This architectural and compiler-level "noise" is then integrated over time by the model's turbulent mixing parameterizations (Baker et al., 2015), leading to the observed divergences in near-surface wind speed and SST. Distinct fluctuation patterns at each station may be linked to track discrepancies between simulations, further highlights COAWST's sensitivity to landfall air-sea interactions. Overall, COAWST(x86) yielded SST RMSE approximately 0.09% lower than COAWST(ARM), possibly due to more conservative numerical solvers on the x86 platform.

4.3 Validation of surface ocean variables against reanalysis and satellite products

To evaluate the performance of COAWST in simulating surface ocean processes on both ARM and x86 platforms, we conducted a joint comparison with the ERA5 reanalysis SST data and AVISO sea level anomaly (SLA) data (Fig.5), and analyzed the corresponding spatial error distributions (Fig.6).

A comparison between model-simulated SST and the ERA5 reanalysis data at 00:00 UTC on July 12 (Fig.5a–c) shows that both COAWST and ERA5 successfully reproduced the cold wake feature trailing the right-rear quadrant of Typhoon Soulik's track, with a minimum temperature around 27 °C. This cooling feature is consistent with enhanced upper-ocean vertical mixing under strong typhoon forcing (Liu et al., 2022). Non-breaking surface waves may further contribute to upper-ocean mixing (Qiao et al., 2004), while the associated SST cooling can reduce oceanic heat supply to the atmosphere and exert a negative feedback on tropical-cyclone intensity (Schade and Emanuel, 1999). However, ERA5 (Fig.5a) failed to capture surface cooling near the typhoon eyewall due to cloud interference and its limited spatiotemporal resolution (Liu et al., 2022), highlighting its limited responsiveness to short-term dynamics.

COAWST tended to underestimate SST in parts of the Pacific and South China Sea northeast of the typhoon track, with a maximum bias of -1.901 1 °C in COAWST(x86) (Fig.6c). Conversely, SST was overestimated on the right side of the track and in some coastal areas, with the largest bias of +2.391 6 °C in COAWST(ARM) near northeastern Taiwan, China (Fig.6a). The overestimation along the right flank may be attributed to the simulation

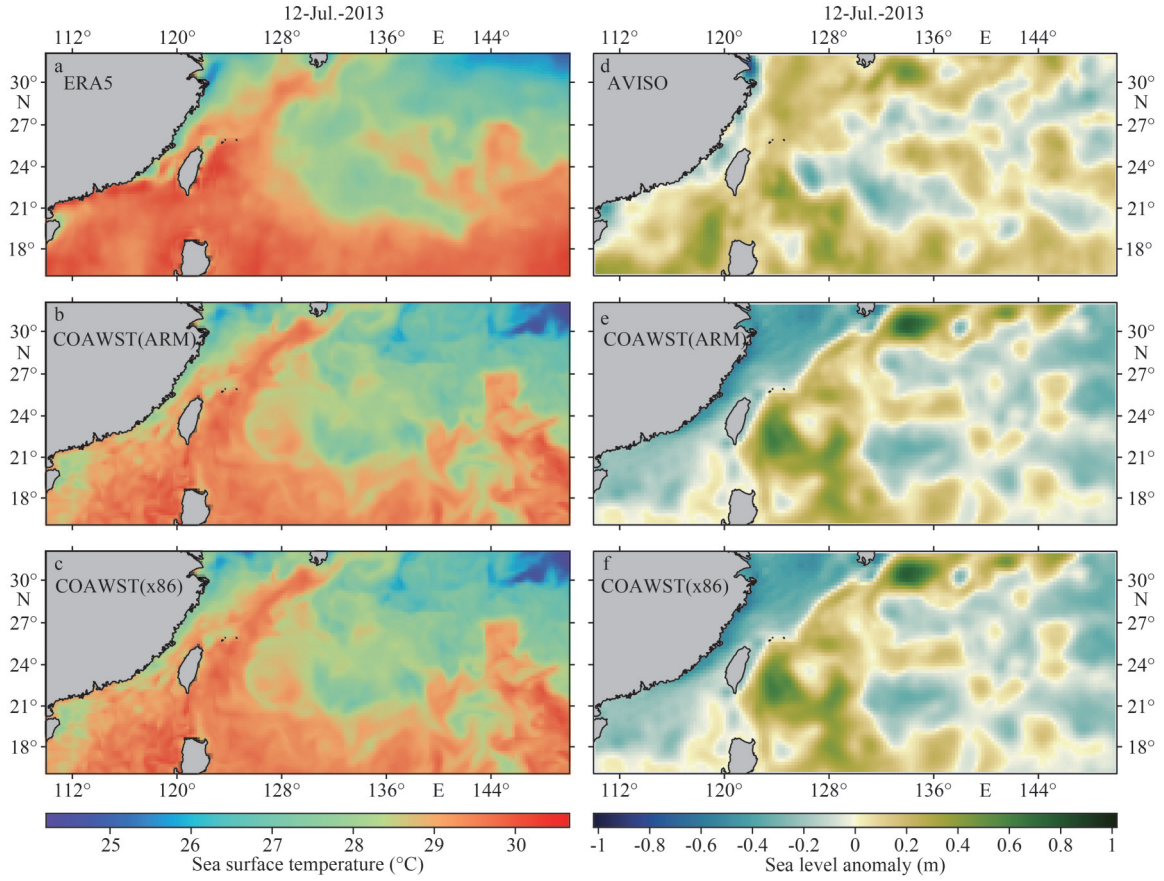


Fig.5 Comparison of simulated and reference sea surface fields on 12 July 2013

a–c. instantaneous sea surface temperature (SST) at 00:00 UTC from ERA5 reanalysis (a), COAWST(ARM) (b), and COAWST(x86) (c); d–f. daily-mean sea level anomaly (SLA) from AVISO (d), COAWST(ARM) (e), and COAWST(x86) (f).

starting at the peak intensity of Soulik, thereby missing early-stage cold wake development. Additionally, spatiotemporal discrepancies between satellite observations and model outputs likely contributed to the observed deviations. Coastal SST overestimation may also result from mismatches between boundary conditions and actual conditions.

The model-simulated sea surface height was processed through daily averaging and detrending (i.e., subtracting the long-term mean sea level over the simulation period) to derive the model's sea level anomaly. This processed output was then compared with the daily AVISO SLA data (Fig.5d–f). Both model configurations (Fig.5e, f) captured the storm-induced sea level anomaly on July 12, generating a distinct sea surface height gradient with broader extrema than observed in AVISO (Fig.5d). This was primarily due to the initial model sea level being lower than observed, resulting in consistent underestimation along the continental margin outside the main storm region. Between the platforms, COAWST(ARM) produced slightly weaker extrema than COAWST(x86), with a

maximum difference of 0.000 3 m.

In terms of spatial error patterns, the largest RMSE occurred near the Changjiang (Yangtze) River estuary (approximately 0.8 m; Fig.6f, h), while errors along the typhoon path were lower (<0.3 m), reflecting the nonlinear response of ocean topography to storm-induced processes. Despite localized discrepancies, COAWST effectively reproduced the spatial distribution, magnitude, and storm-induced variations of surface ocean variables on both platforms.

The RMSEs of SST compared with ERA5 were 0.536 0 °C for COAWST(ARM) and 0.536 5 °C for COAWST(x86). For SLA, both configurations yielded RMSEs of 0.215 0 m relative to AVISO. These results confirm that COAWST, particularly on the ARM-based platform, demonstrates high reliability in simulating storm surge and related ocean surface fields under coupled conditions.

To comprehensively evaluate the performance of COAWST on ARM and x86 platforms, Taylor diagrams were used to quantify the agreement between model outputs and observational data for key atmospheric and oceanic variables, including

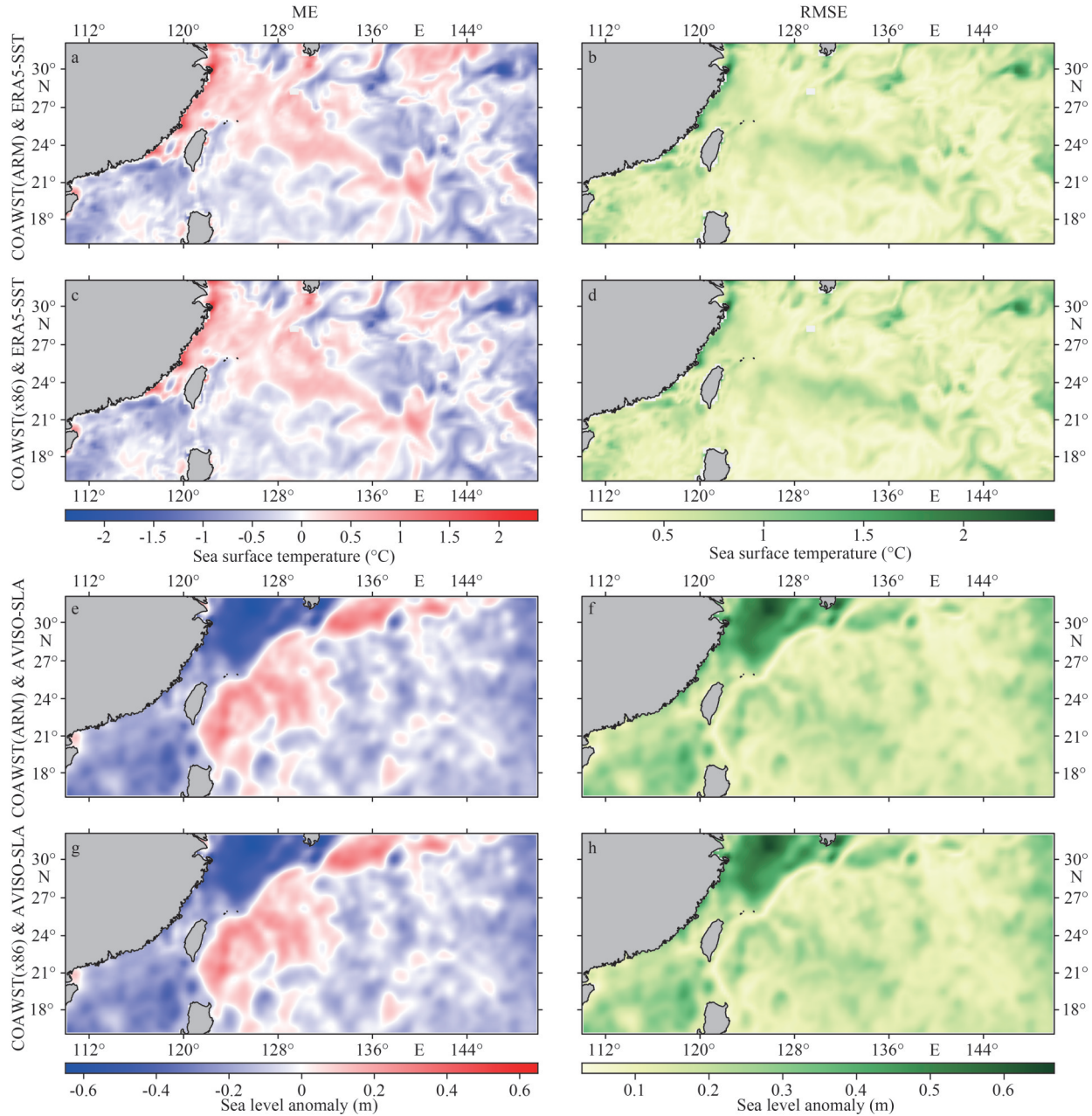


Fig.6 Spatial distribution of errors between COAWST simulations and reference data

a–d. sea surface temperature (SST) errors relative to ERA5: COAWST(ARM) mean error (ME) and root mean square error (RMSE) (a, b), COAWST(x86) ME and RMSE (c, d); e–h. sea level anomaly (SLA) errors relative to AVISO: COAWST(ARM) ME and RMSE (e, f) and COAWST(x86) ME and RMSE (g, h). In this section, the ME maps are obtained by subtracting the corresponding reference datasets (ERA5 for SST and AVISO for SLA) from COAWST outputs and then temporally averaging the results.

SP, wind speed, SST, and SLA (Fig.7). Detailed statistics are summarized in Table 3.

For SP and wind speed, both COAWST simulations exhibited high correlations with station observations ($R > 0.9$), with RMSEs around 2.6 and standard deviations comparable to those of the observations, indicating reliable model performance for these meteorological variables. The correlation between model-simulated SST and station observations

was relatively low ($R \approx 0.35$), but significantly improved when compared with ERA5 data ($R \approx 0.88$). Based on the positions of model results in the Taylor diagrams, COAWST(ARM) demonstrated slightly better skill than COAWST(x86) in simulating wind speed, SST, and SLA, though it showed slightly weaker performance in sea level pressure simulation. These results suggest that COAWST running on ARM-based systems has good numerical

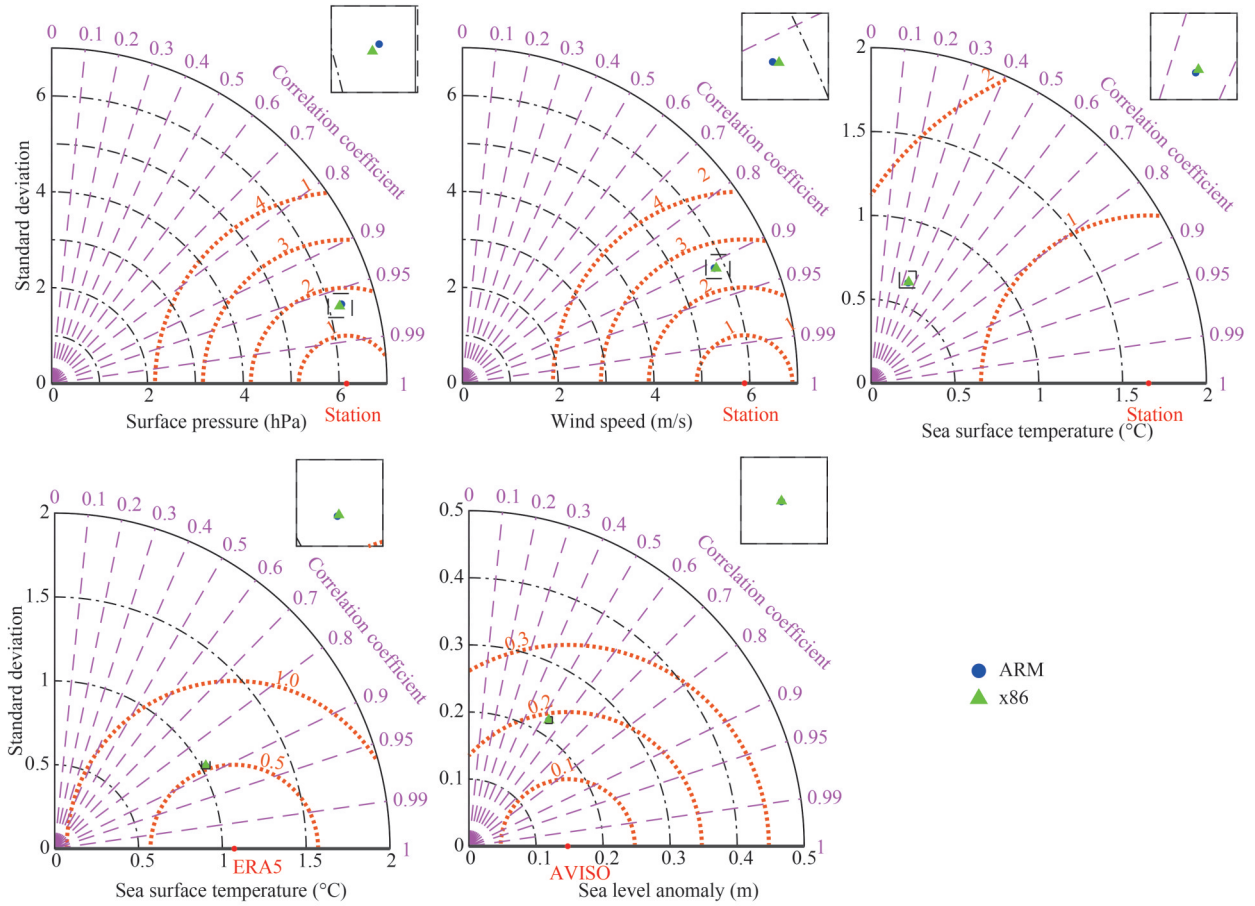


Fig.7 Taylor diagrams comparing COAWST(ARM) and COAWST(x86) simulations with station and satellite observations
Red contours indicate RMSE, black contours denote standard deviation, and angular position corresponds to correlation coefficient. Insets in the upper right corners of each panel show magnified views of the enclosed dashed rectangles.

Table 3 Standard deviation (σ), root mean square errors (RMSEs), and correlation coefficient (R) between COAWST simulations and observational datasets

Statistical metrics	Surface pressure (hPa)		Wind speed (m/s)		Sea surface temperature (°C)				Sea level anomaly (m)	
	Station		Station		Station		ERA5		AVISO	
	ARM	x86	ARM	x86	ARM	x86	ARM	x86	ARM	x86
σ	6.273 3	6.225 3	5.784 7	5.816 6	0.638 6	0.643 0	1.026 7	1.027 7	0.222 4	0.222 5
RMSE	2.577 7	2.573 3	2.583 5	2.589 4	2.988 1	2.985 4	0.536 0	0.536 5	0.215 0	0.215 0
R	0.964 5	0.965 7	0.909 7	0.911 1	0.345 7	0.348 3	0.877 0	0.876 9	0.535 6	0.535 5

stability and robust capability in resolving complex coupled physical processes, making it suitable for high-resolution simulations and integrated satellite-model analyses.

4.4 Multivariable ocean response error analysis

This section examines the differences in simulated oceanic fields between ARM and x86 platforms by analyzing the spatiotemporal error patterns in key ocean variables. The analysis also considers how these errors relate to inter-component coupling and the thermodynamic-dynamic structure

of Typhoon Soulik during its peak intensity.

Figure 8 illustrates the spatiotemporal error characteristics of thermal and dynamic ocean variables (e.g., SST, surface stress, sea surface height, surface velocity) simulated by COAWST on ARM and x86 platforms. The spatial ME distribution of thermal variables such as SST was relatively scattered, with alternating positive and negative ME values between the platforms. A localized maximum in MAE was observed north of Taiwan, China. Temporally, RMSE fluctuated due to the influence of climatological constraints applied every 24 h,

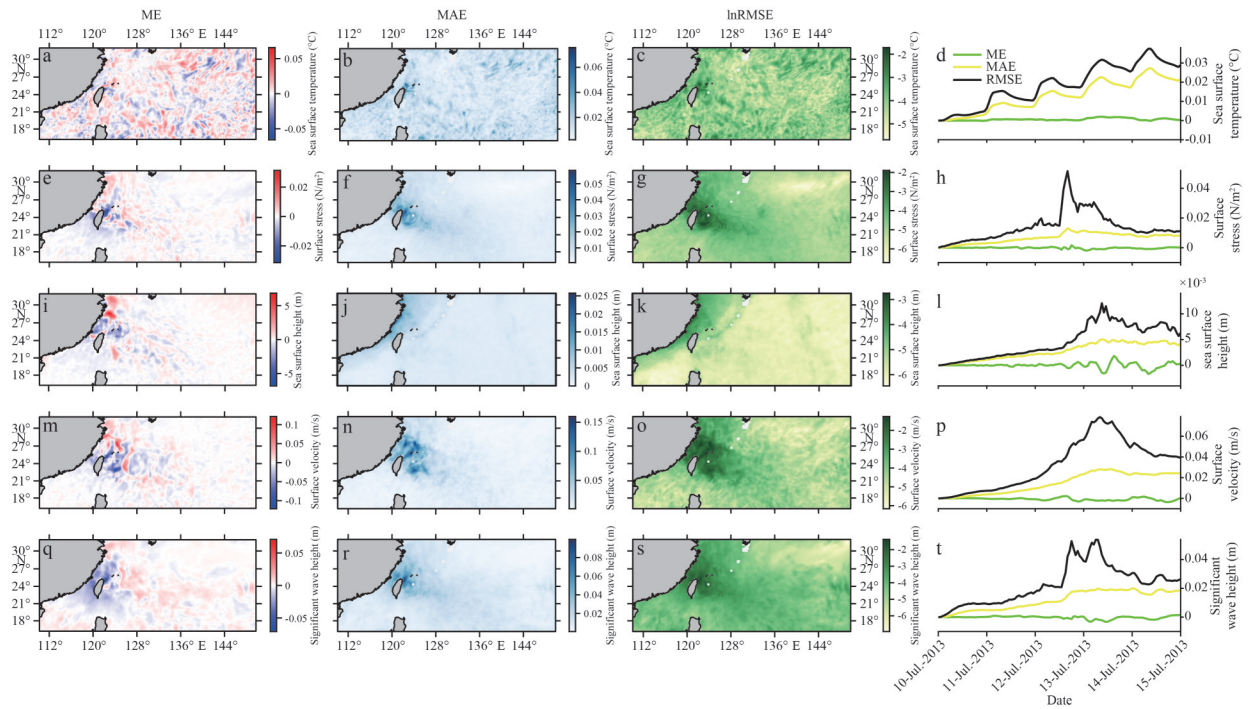


Fig.8 Spatial and temporal distributions of differences between COAWST(ARM) and COAWST(x86) simulations for key oceanic variables

a–d. sea surface temperature; e–h. surface stress; i–l. sea surface height; m–p. surface velocity; q–t. significant wave height. The error metrics shown for each variable are spatial mean error (ME), mean absolute error (MAE), natural logarithm of the root mean square error (lnRMSE), and the temporal RMSE series. The ME maps are calculated as COAWST(ARM) minus COAWST(x86).

reaching a minimum of 0.028 9 °C on July 15. The MAE of SST closely matched the RMSE, and the absolute bias between the two platforms was nearly identical, suggesting the presence of systematic errors attributable to the underlying numerical architecture. The SST simulations from both platforms were highly correlated ($R^2=0.999\ 6$). When combined with satellite validation, COAWST (ARM) exhibited slightly better performance in simulating thermal fields. Given SST's dominant role in regulating heat fluxes, even subtle differences in its simulation may propagate and accumulate in the dynamic fields.

The spatial error of dynamic variables was more localized, with similarities and distinctions observed among different variables. Surface stress, surface velocity, and significant wave height (SWH) shared similar RMSE patterns, concentrated near the typhoon track, particularly in the northeastern waters off Taiwan, China, and decayed outward. Compared to surface stress, SWH exhibited a broader negative ME range and larger error extrema around Taiwan, China, likely due to wind field asymmetries, island-induced blocking effects, and wave refraction or dissipation, all of which may be amplified differently on ARM and x86 architectures.

Surface velocity errors were influenced by multiple factors including sea surface height variations, storm surge, and swell, leading to the largest error range among all dynamic variables.

The spatial ME distributions of sea surface height and surface velocity revealed coherent patterns: negative ME around Taiwan, China, and positive ME near the Changjiang River estuary. This suggests that sea surface height errors may influence surface circulation through dynamic coupling processes. Furthermore, the spatial error structure of sea surface height highlighted differential responses to topography and boundary conditions between platforms. East of the Ryukyu Islands, model results were consistent across platforms. However, west of the islands, COAWST(ARM) slightly overestimated values near the Changjiang River mouth ($ME \approx +0.006\ m$), and underestimated near northern Taiwan, China ($ME \approx -0.004\ m$). MAE decreased seaward from the continental margin, peaking at approximately 0.025 7 m. These discrepancies are likely associated with tidal effects, particularly in shallow, topographically complex regions where non-linear interactions such as bottom friction and tidal asymmetry are significant. Minor differences in floating-point precision between platforms may be

amplified by these nonlinear processes.

In terms of temporal evolution, RMSEs for all dynamic ocean variables exhibited pronounced peaks corresponding to typhoon development. In early stages, errors accumulated due to continuous coupling between model components and differing numerical treatments of physical variables across platforms. As Soulik approached Taiwan, China, physical complexity increased sharply, and RMSEs for surface stress and SWH surged beyond 0.05. This indicates that in regions of strong air-sea interaction, discrepancies in numerical precision between computing platforms are more rapidly magnified. RMSEs of sea surface height and surface velocity rose subsequently, peaking just before landfall along with SWH. After landfall, air-sea coupling weakened, and RMSEs declined. Throughout the simulation, errors remained within the 10^{-2} magnitude, suggesting that numerical divergence is most active in dynamic regions and tends to converge during more stable conditions.

Figure 9 further elucidates the intrinsic relationship between error propagation and the correlation of coupled variable exchanges across model components. On both platforms, the inter-module transfer of SWH from WW3 to WRF and ROMS exhibits extremely high correlation ($R^2 > 0.9999$), with negligible influence from the typhoon. Variables transferred from ROMS and WRF to WW3, as well as SST from ROMS to WRF, show improved correlation in regions heavily affected by the typhoon, whereas the correlation for SP transferred from WRF to ROMS is comparatively weaker. COAWST(ARM) exhibits slightly lower inter-model correlation than COAWST(x86), especially for wind speed and current vectors. This discrepancy corresponds spatially to areas of strong wind forcing northeast of Taiwan, China, suggesting that even a minor decline in coupling correlation may facilitate the transmission and amplification of dynamical errors across model components.

To more clearly isolate spatial structural differences in platform-induced error and to avoid artifacts arising from mismatches between initial conditions and historical observations, Fig.10 presents a cross-sectional analysis of radial circulation during the peak phase of Typhoon Soulik (from 05:00 July 10 to 00:00 July 11; Fig.3). Both model versions captured the strong tangential winds near the eyewall, with maximum velocities occurring at 850 hPa and a radius of 87.5 km. COAWST(x86) simulated a higher peak tangential wind than COAWST(ARM) by

approximately 0.0379 m/s, with more concentrated intensity, whereas COAWST(ARM) produced a slightly broader and more diffuse high-wind zone, indicating a marginal underestimation of typhoon intensity. In the mid-lower troposphere (900–700 hPa) and upper troposphere (300–200 hPa), COAWST(x86) exhibited stronger circulation, suggesting enhanced sensitivity to large-scale forcing, while COAWST(ARM) showed better response in the lower boundary layer (950 hPa). Thermodynamically, COAWST(x86) produced a more concentrated warm core near the surface, whereas COAWST(ARM) demonstrated a tighter warm core at higher altitudes. Errors between the two simulations were primarily confined within a 150-km radius, aligning with the primary circulation zone, underscoring the influence of numerical accuracy on simulated storm structure.

These results indicate that COAWST simulations on the ARM platform are generally comparable in credibility to those on x86, and even exhibit enhanced stability and resolution in thermodynamic and near-surface dynamical responses. Conversely, COAWST(x86) demonstrates slight advantages in resolving upper-level circulation structures and coupling consistency under strong typhoon forcing. These differences may be related to platform-dependent architectural factors, including compiler optimization, floating-point operation ordering, memory-system behavior, and parallel reduction or synchronization. Specifically, the NUMA-aware optimizations and HMPI library on the ARM platform potentially led to different inter-process communication latencies during the halo exchange in COAWST's advection schemes. This minutely alters the timing of when boundary data is available for calculations, creating a different numerical trajectory. Similarly, the handling of denormal numbers (extremely small values near zero) in the turbulence closure schemes can differ between the ARM and x86 floating point units. In regions of strong shear near the eyewall, these low-level numerical distinctions can be amplified, influencing the simulated storm structure and coupling fidelity. Such architectural distinctions have a measurable impact on variable transfer accuracy and error accumulation, particularly under high-resolution, strongly nonlinear processes. The combined effects of spatiotemporal error propagation, inter-model variable correlation, and typhoon structure reproduction form the key mechanisms driving multivariable differences between ARM and x86 platforms.

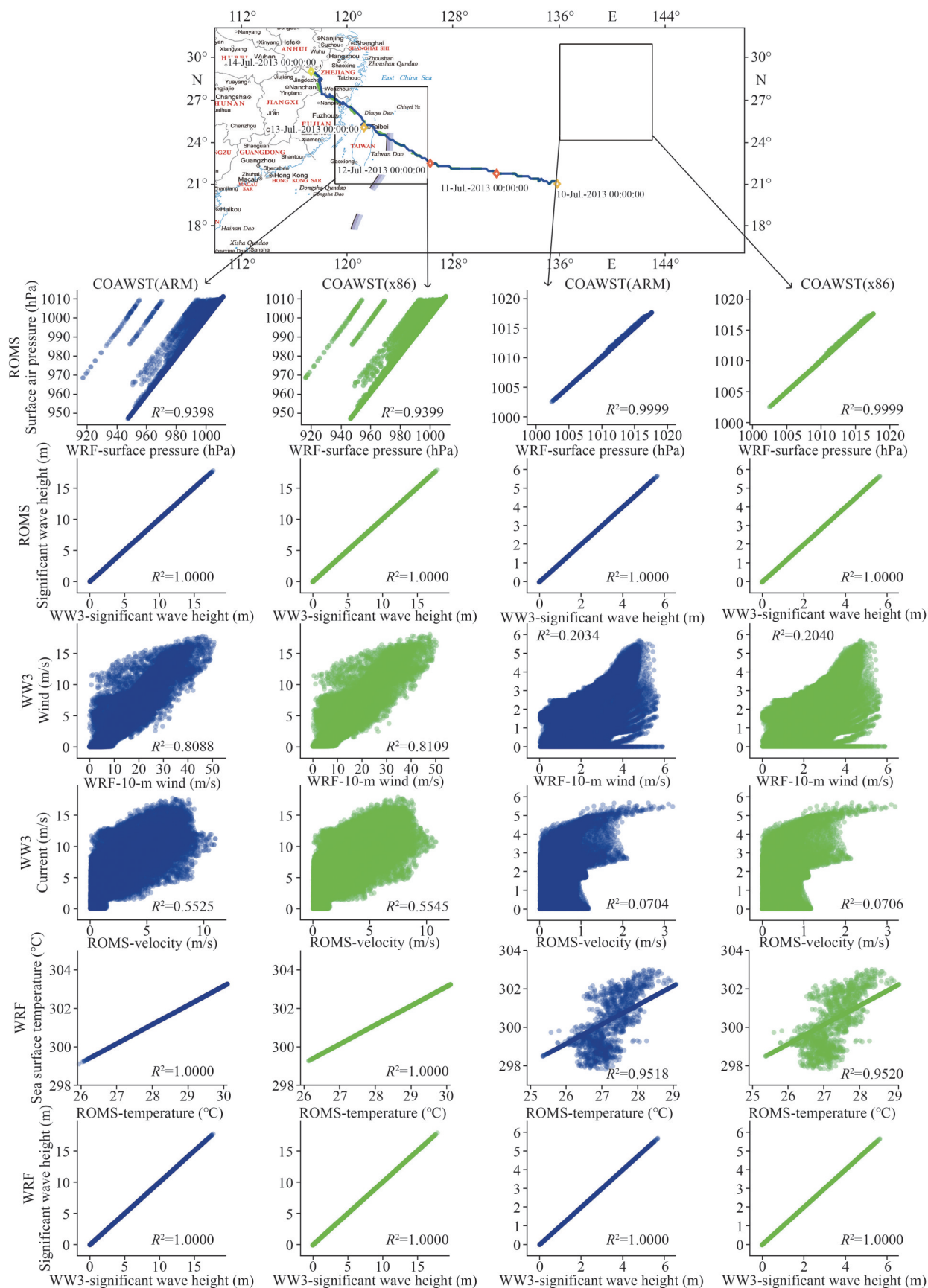


Fig.9 Correlation coefficients for coupled variable exchanges between COAWST(ARM) and COAWST(x86) at various typhoon-affected locations

COAWST(ARM) in blue, and COAWST(x86) in green. The x-axis represents the source model, and the y-axis represents the recipient model for variable transfer.

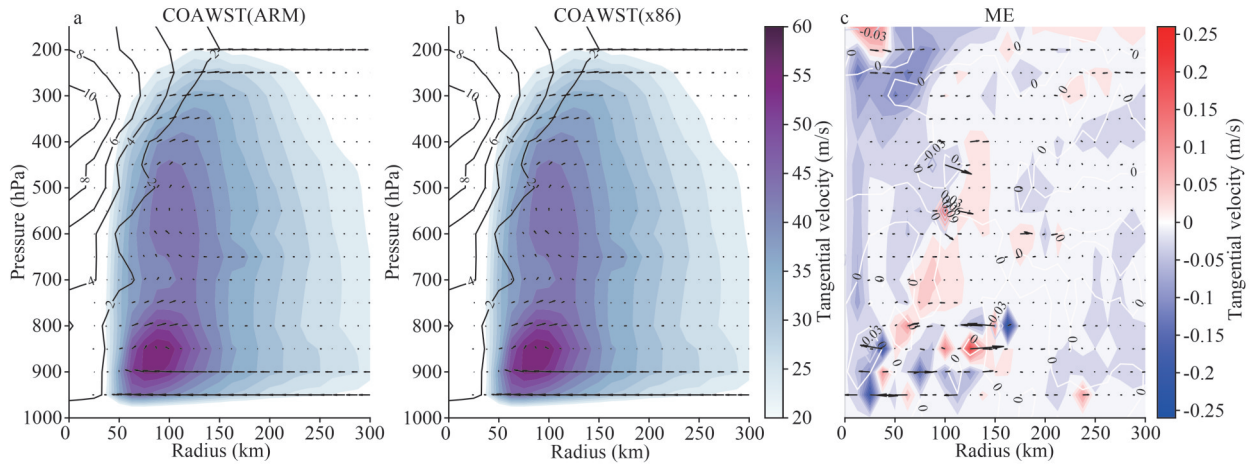


Fig.10 Radius-pressure cross-sections of azimuthally and temporally averaged structure of Typhoon Soulik during the 19-h peak stage (July 10 05:00–July 11 00:00) for COAWST(ARM) and COAWST(x86) simulations

See Fig.3 for typhoon intensity. Shading represents tangential velocity (m/s). Vectors indicate radial velocity (m/s) and vertical velocity (Pa/s), with the scale shown in the bottom left corner. Contours show potential temperature anomalies (K), defined as deviations from the radial mean.

5 CONCLUSION

This study leverages the high-performance capabilities of ARM-based Kunpeng processors and the advanced algorithmic design of the COAWST model to simulate Typhoon Soulik (2013) on the Huawei Atlas 900 cluster. The results are compared against simulations performed on an Intel x86-based platform (Sugon cluster) using the same model configuration. Both sets of simulation results were cross-validated against observational datasets, including historical typhoon records, in situ measurements, and multi-source satellite products. The primary goal is to assess the impact of computing architecture on high-resolution air-sea coupled simulations, with a focus on computational efficiency, model accuracy, spatiotemporal error structures, inter-component coupling fidelity, and physical process representation, thereby providing scientific support for ARM's application in Earth system modeling.

Results show that under identical model configurations and parallel settings, the ARM platform reduced computation time by approximately 15.44% compared to x86, with only marginal differences in simulation accuracy. This improvement is attributed to ARM's highly parallel multi-core design, optimized memory communication, and compiler-level adaptations for the COAWST structure, highlighting ARM's potential in high-resolution Earth system modeling.

Both platforms effectively captured Typhoon Soulik's track, intensity evolution, and storm surge features, showing high consistency with observational

data (pressure and wind $R > 0.9$; SST $R \approx 0.88$ with ERA5). Simulated ocean-atmosphere variables from both platforms displayed strong agreement, with $R^2 > 0.99$ and RMSE values remaining within 10^{-1} – 10^{-3} ranges (Table 4), affirming COAWST(ARM)'s reliability. Furthermore, COAWST(ARM) achieved marginal improvements in nearshore wind speed (RMSE reduced by 0.23% against station observations) and regional SST simulations (RMSE reduced by 0.09% relative to ERA5 reanalysis), suggesting enhanced numerical stability in specific physical fields. Notably, the coastal SST comparison revealed a slight advantage for the x86 platform, underscoring the importance of distinguishing nearshore local effects from basin-scale reanalysis constraints.

Thermal variable errors were spatially more diffuse, while dynamical variables exhibited concentrated errors in high-response regions near the typhoon. Differences in dynamical variable error patterns revealed subtle distinctions in terrain response and

Table 4 Comparison of R^2 and RMSE values for COAWST simulations on ARM and x86 platforms across key variables

Variable	R^2	RMSE
Surface pressure	0.999 9	0.143 3 hPa
Wind	0.993 7	0.327 3 m/s
Sea surface temperature	0.999 6	0.021 6 °C
Surface stress	0.997 5	0.016 9 N/m ²
Sea surface height	0.999 9	0.005 6 m
Surface velocity	0.997 6	0.040 6 m/s
Significant wave height	0.999 8	0.026 4 m

boundary condition treatments between platforms. RMSE time series peaked during typhoon intensification and landfall phases and gradually subsided afterward, indicating the joint effects of error accumulation under high dynamics and boundary forcing.

Analysis of inter-component error propagation showed that while overall coupling correlations were similar between platforms, the ARM system exhibited slightly reduced coupling fidelity for key dynamical variables (e.g., wind, current vectors), especially in strongly forced regions, suggesting potential for localized error amplification during model exchange processes. Additionally, differences in simulated radial circulation and thermodynamic structures indicated that hardware architecture can affect the physical realism of typhoon reproduction, x86 performed slightly better in upper-level storm structure, while ARM showed stronger and more stable boundary-layer responses.

In summary, COAWST on ARM delivers not only superior computational performance but also comparable or slightly better accuracy than x86 in simulating high-resolution coupled ocean-atmosphere processes. This supports the feasibility of deploying ARM-based systems for next-generation Earth system modeling, climate studies, and extreme weather event forecasting. Similarly, this study demonstrates that computing architecture is one quantifiable source of uncertainty in high-resolution Earth system modeling. The observed discrepancies between ARM and x86 platforms are not random but systematically tied to low-level numerical factors: diverging compiler optimizations, floating-point operation ordering, memory hierarchy performance, and the handling of extreme values. These factors interact with non-linear physics of the model. Consequently, cross-platform validation should be incorporated into the quantitative research of numerical simulations to quantify this architectural uncertainty and enhance the robustness of scientific conclusions, especially for extreme weather simulations.

Nevertheless, limitations remain. This study focused on a single storm event, limiting the generalizability across different storm types and seasonal backgrounds. Additionally, communication bottlenecks and large-scale parallel scaling on ARM were not thoroughly evaluated. Future work should expand simulations to multiple storm cases, spatial domains, and resolutions to systematically assess ARM's numerical stability and explore its broader potential in complex coupled system modeling.

6 DATA AVAILABILITY STATEMENT

Data will be made available on request.

7 ACKNOWLEDGMENT

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