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Original Empirical Research

Hybrid Modelling of Extreme Storm Processes and Navigation Risks in the Azov Sea Based on Three-Dimensional Hydrodynamics and Machine Learning Methods

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Abstract

Introduction. Extreme storms with wind speeds exceeding 30–35 m/s pose a significant threat to navigation and coastal infrastructure in the Azov Sea. The complex bathymetry, shallow water, and coastal geometry amplify wave and surge effects, causing severe destruction. The increasing frequency of extreme weather events requires next-generation forecasting systems capable of capturing nonlinear multiscale interactions between wind, waves, and currents.

Materials and Methods. A hybrid approach was developed, combining three-dimensional numerical hydrodynamic modelling based on the Navier-Stokes equations with Large-Eddy Simulation (LES) turbulence closure, ensemble probabilistic forecasting, and machine learning methods — including Physics-Informed Neural Networks (PINNs) and Fourier Neural Operators (FNOs). Atmospheric and oceanographic data from ERA5 and CMEMS reanalyses were used to reconstruct storm scenarios for 2010–2024. Ship-wave interactions were modeled in six degrees of freedom, while coastal infrastructure fragility was evaluated using probabilistic vulnerability curves. Validation was performed using Sentinel-1/3 satellite data processed by the "LBP-neural_network" software package and Copernicus Marine Service products.

Results. Three representative storm scenarios were simulated. The significant wave height in the central Azov Sea reached up to 5.2 m, with surge amplitudes up to 1.5 m. The most hazardous conditions occurred in the Kerch Strait, where current velocities reached 1.1 m/s. Under wind speeds of 30–35 m/s, the probability of exceeding the critical 4 m wave height was 42%. Resonant ship motions with roll amplitudes up to 25° were detected, indicating a high capsizing risk. Risk maps identified the most vulnerable zones near Taganrog, Yeysk, and Port Kavkaz. The integration of PINNs and FNOs accelerated ensemble simulations by a factor of 10–12 while maintaining prediction errors below 8%.

Discussion. The proposed hybrid methodology proved highly effective for modelling extreme hydrodynamic processes and navigation risks. The LES framework accurately reproduced wave breaking and vortex generation processes, while coupling with neural network surrogates combined physical consistency with computational efficiency.

Conclusion. The approach improved forecast accuracy by 25–30% compared with conventional spectral models (SWAN, WAVEWATCH III). The results provide a scientific basis for developing early warning systems, assessing navigation safety, and planning coastal protection measures in the Azov–Black Sea region.

Keywords: Azov Sea, extreme storms, three-dimensional hydrodynamics, machine learning, physics-informed neural networks, Fourier neural operators, navigation risk, large-eddy simulation, coastal infrastructure, storm forecasting

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Оригинальное эмпирическое исследование

Гибридное моделирование экстремальных штормовых процессов и рисков судоходства в Азовском море на основе трёхмерной гидродинамики и методов машинного обучения

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Аннотация

Введение. Экстремальные штормы со скоростью ветра более 30–35 м/с представляют серьёзную угрозу для судоходства и прибрежной инфраструктуры Азовского моря. Сложная батиметрия, мелководье и конфигурация береговой линии усиливают волновые и нагонные процессы, вызывая разрушительные последствия. В связи с прогнозируемым увеличением частоты экстремальных погодных явлений актуальной задачей является развитие методов прогнозирования, учитывающих нелинейные и многомасштабные взаимодействия волн, ветра и течений.

Материалы и методы. Разработан гибридный подход, объединяющий трёхмерное численное моделирование на основе уравнений Навье-Стокса с крупновихревой моделью турбулентности (LES), ансамблевое вероятностное прогнозирование и методы машинного обучения — физически информированные нейронные сети (PINNs) и операторы Фурье (FNOs). Атмосферные и океанографические данные реанализа ERA5 и CMEMS использованы для реконструкции штормовых сценариев 2010–2024 гг. Взаимодействие волн с судами описано в шести степенях свободы. Для анализа уязвимости применены кривые фрагильности инфраструктуры. Верификация проведена по спутниковым данным Sentinel-1/3 обработанными программным комплексом «LBP-neural_network» и продуктам Copernicus Marine Service.

Результаты исследования. Моделирование трёх сценариев показало, что значительная высота волн в центральной части Азовского моря достигает 5,2 м, а уровень нагонов — 1,5 м. Наиболее опасные условия формируются в Керченском проливе, где скорости течений достигают 1,1 м/с. При скорости ветра 30–35 м/с вероятность превышения критической высоты волны 4 м составляет 42 %. Выявлены резонансные режимы колебаний судов с амплитудой крена до 25°, что создаёт угрозу опрокидывания. Карты риска показали зоны максимальной уязвимости портов Таганрог, Ейск и Кавказ. Применение PINNs и FNO позволило ускорить ансамблевые расчёты в 10–12 раз при сохранении точности на уровне менее 8 %.

Обсуждение. Предложенная гибридная методология демонстрирует высокую эффективность при моделировании экстремальных гидродинамических процессов и рисков судоходства. LES корректно воспроизводит процессы волнового обрушения и генерации вихрей, а интеграция с нейросетевыми моделями обеспечивает сочетание физической строгости и вычислительной эффективности.

Заключение. Метод способен повысить точность прогнозов на 25–30 % по сравнению с традиционными моделями SWAN и WAVEWATCH III. Полученные результаты могут быть использованы для разработки систем оперативного предупреждения, оценки навигационной безопасности и планирования природоохранных мероприятий в Азово-Черноморском регионе.

Ключевые слова: Азовское море, экстремальные штормы, трёхмерная гидродинамика, машинное обучение, PINNs, FNO, риск судоходства, LES-моделирование, прибрежная инфраструктура, прогнозирование штормов

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Introduction. Extreme storms with wind speeds exceeding 30–35 m/s are among the most destructive manifestations of atmospheric forcing in coastal and marine areas. They cause severe damage to port facilities, coastal protection structures, residential and recreational zones, and also pose a significant threat to maritime navigation, frequently leading to shipwrecks and cargo loss. In the context of climate change, an increase in the frequency and intensity of such storms is projected, thereby amplifying their socio-economic and environmental impacts. This underscores the necessity for developing next-generation forecasting methods capable of accounting for multi-scale interactions between storms and waves.

Currently, operational forecasting systems are primarily based on spectral wave models, such as SWAN, WAM, and WAVEWATCH III, which provide reliable large-scale estimates of wave energy distribution [1–3]. However, their spatial resolution is insufficient for accurately describing the nonlinear transformation of waves in shallow and semi-enclosed seas. In critically important areas, such as the Sea of Azov and the Kerch Strait, complex bathymetry, coastline configuration, and resonance effects lead to the amplification of wave energy and an underestimation of storm risks [4]. Furthermore, the interaction between extreme waves and ships and coastal infrastructure involves complex three-dimensional hydrodynamic processes (refraction, diffraction, wave breaking, and turbulence) that cannot be fully reproduced by two-dimensional or simplified models [5].

Recent advances in computational fluid dynamics (CFD) and high-performance computing have enabled the development of three-dimensional non-hydrostatic models capable of explicitly simulating turbulence, shallow-water wave transformation, and their nonlinear interaction with structures [6]. The integration of such models with machine learning methods, including neural networks trained on reanalysis data and buoy observations, opens up new possibilities for adaptive forecasting and risk assessment [7]. However, the comprehensive integration of CFD modelling, artificial intelligence techniques, and coastal risk analysis remains insufficiently explored, particularly concerning the semi-enclosed basins of the Azov-Black Sea region.

Ensuring ship safety under extreme storm conditions remains a challenging scientific problem. The International Maritime Organization (IMO) has recently approved second-generation intact stability criteria, defining key failure modes: parametric rolling, surf-riding, and broaching [8]. Research indicates that resonance between long-period storm waves and a vessel's natural frequencies can lead to catastrophic consequences, as exemplified by the accident of the tanker Prestige [9]. Numerical experiments confirm that steep shallow-water waves in straits can cause loss of controllability and capsizing even of modern vessels [10].

Regional studies highlight the particular vulnerability of the Sea of Azov and the Kerch Strait, where shallow depths and complex bottom topography enhance refraction effects and the formation of standing waves, leading to a local increase in wave height [11−12].

Beyond hydrodynamic aspects, increasing attention is being paid to infrastructure vulnerability, including the probabilistic fragility analysis of port and coastal protection structures [13], as well as ecosystem-based approaches emphasizing the protective role of seagrass meadows and other natural features. Despite the progress achieved, significant gaps persist: operational models underestimate the impacts of storms in shallow seas; the integration of three-dimensional hydrodynamics and machine learning methods is limited; and vulnerability criteria for ships under the combined action of wind, waves, and currents are inadequately developed. The present study aims to address these gaps and proposes a hybrid modelling concept for forecasting extreme storms and their consequences in the Azov-Black Sea region, with a focus on navigation safety and coastal infrastructure resilience.

Materials and Methods. The methodology of this research is based on a multi-level hybrid approach that integrates numerical hydrodynamic modelling, machine learning, physics-informed neural networks, ensemble probabilistic forecasting, and GIS risk mapping.

The flow field is described by the Navier-Stokes equations for an incompressible fluid with a free surface [14]:

$$\nabla \cdot \mathbf{u} = 0,$$

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} = -\frac{1}{\rho}\nabla p + \nu \nabla^2 \mathbf{u} + \mathbf{g} + \nabla \cdot \boldsymbol{\tau}_t + \mathbf{F}_{\text{wind}},$$

where $\mathbf{u}$ is the velocity vector (m/s); p is the hydrodynamic pressure (Pa); ρ is the water density (kg/m³); ν is the kinematic viscosity (m²/s); $\mathbf{g}$ is the gravitational acceleration vector (m/s²); $\boldsymbol{\tau}_t$ are the subgrid-scale turbulent stresses (Pa); $\mathbf{F}_{\text{wind}}$ is the wind forcing (N/m³).

This approach accounts for the nonlinear interaction of waves and currents, as well as wave shoaling and breaking phenomena, which are critical for shallow seas such as the Azov Sea and the Kerch Strait. Unlike spectral models, it resolves local nonlinearities.

Turbulence is described using the Large Eddy Simulation (LES) method with the Smagorinsky closure [15]:

$$\tau_{ij} = -2\nu_t S_{ij}, \;\; \nu_t = (C_s \Delta)^2 \,|\, S \,|,$$

where τ_{ij} are the subgrid-scale Reynolds stresses; S_{ij} is the rate-of-strain tensor; ν_t is the eddy viscosity; C_s is the Smagorinsky constant; Δ is the filter width (grid scale).

LES ensures the correct reproduction of wave breaking, vortices, and turbulent bursts in shallow and semi-enclosed seas. This method resolves large-scale turbulence governing wave breaking and vortex generation during storms, while only modelling small-scale dissipation. This provides higher accuracy compared to RANS for extreme and transient processes.

The momentum transfer from the atmosphere to the ocean is parameterized as follows [16]:

$$\mathbf{F}_{\text{wind}} = \frac{\rho_a C_D \,|\, \mathbf{U}_{10} \,|\, \mathbf{U}_{10}}{\rho},$$

where ρ_a is the air density; C_D is the drag coefficient; $\mathbf{U}_{10}$ is the wind speed at 10 m height. At wind speeds of 30–35 m/s, a strong atmosphere-ocean coupling develops. This parameterization directly couples atmospheric models (WRF, COSMO-Ru) with hydrodynamics, ensuring realistic wave growth.

The interaction of storm waves with ships and infrastructure is modeled using the rigid body dynamics equations [17]:

$$M\ddot{\mathbf{X}} + C\dot{\mathbf{X}} + K\mathbf{X} = \mathbf{F}(t),$$

where **X** represents displacements in six degrees of freedom (surge, sway, heave, roll, pitch, yaw); M is the mass matrix; C is the damping matrix; K is the restoring force matrix; $\mathbf{F}(t)$ is the wave excitation force.

The resonance condition for ship safety is expressed as:

$$\omega_w \approx \omega_n,$$

where ω_w is the wave frequency; ω_n is the natural frequency of the ship.

Many maritime disasters have been caused by resonance phenomena (parametric rolling, surf-riding, and broaching). Incorporating ship-wave dynamics enables forecasting not only the storms themselves but also their actual impact on vessels.

Uncertainty is quantified using ensembles of CFD simulations with perturbed wind forcing conditions. The exceedance risk is defined as:

$$P(H > H_{\text{crit}}) = \frac{1}{N}\sum_{i=1}^{N} I\left(H^{(i)} > H_{\text{crit}}\right),$$

which enables the generation of probabilistic risk maps instead of solely deterministic scenarios, where $H^{(i)}$ is the hazard characteristic (e. g., significant wave height) from the i-th ensemble member; N is the ensemble size; I is the indicator function.

Storm forecasting is inherently probabilistic. Ensembles provide the probabilistic forecasts (risk maps) essential for navigation and coastal protection. We integrate Physics-Informed Neural Networks (PINNs) and Fourier Neural Operators (FNOs). PINNs incorporate differential equation constraints into the loss function [18]:

$$\mathcal{L}(\theta) = \|\mathcal{N}[u_\theta] - f\|^2 + \lambda\|u_\theta - u_{\text{obs}}\|^2,$$

ensuring consistency with the Navier-Stokes equations, where $\mathcal{N}$ is the Navier-Stokes operator; u_θ is the neural network prediction; u_{obs} is the observed data; f epresents the source terms (forcing); λ is the weighting coefficient.

Fourier Neural Operators (FNOs) approximate the mappings from atmospheric forcings to wave responses [19]:

$$\hat{u} = \mathcal{G}_\theta(f), \;\; \mathcal{G}_\theta : (\mathbf{U}_{10}, p) \mapsto (H_s, \eta_{\max}),$$

where $\mathcal{G}_\theta$ is the neural network-approximated operator mapping atmospheric inputs f to wave responses $\hat{u}$.

This enables the construction of fast surrogate models for ensemble calculations. PINNs ensure physical law compliance in neural networks, while FNOs learn rapid mappings for ensemble forecasting. This hybrid approach simultaneously achieves both computational speed and physical realism, which is critical for early warning systems.

Finally, simulation results are integrated with infrastructure vulnerability curves:

$$P_{\text{damage}} = \Phi\left(\frac{\ln q_{\text{impact}} - \mu}{\sigma}\right),$$

where q_{impact} is the shock load; μ, σ are vulnerability curve parameters; Φ is the standard normal cumulative distribution function.

This enables the generation of spatial risk maps for ship casualties and infrastructure damage zones in the Sea of Azov, Kerch Strait, and Black Sea. For numerical discretization, the pressure correction method [20] was employed, ensuring mass conservation at each time step through iterative updates of velocity and pressure fields. The developed hybrid methodology, combining Computational Fluid Dynamics (CFD) and Artificial Intelligence (AI) techniques, enables high-accuracy probabilistic forecasting of storm surges and navigational risks in the Azov and Black Seas.

Results. The methodology employed a multi-level hybrid approach, integrating numerical free-surface modelling based on the Navier-Stokes equations, parameterization of atmospheric forcing, Large Eddy Simulation (LES), ensemble forecasting, and the incorporation of neural network approximators (PINNs, FNOs) to accelerate computations.

Three characteristic scenarios were defined for the numerical experiments:

• **Scenario 1 (Moderate-intensity storm):** Wind speed of 15–21 m/s, north-easterly direction, duration of 12 hours. This scenario accounts for water level fluctuations with an amplitude of up to 0.4 m.

• **Scenario 2 (Extreme storm):** Wind speed of 29–37 m/s, easterly direction, duration of 24 hours. This leads to the formation of wind-setup and surge phenomena, with growth in the significant wave height H_s.

• **Scenario 3 (Anomalous cyclonic storm):** Wind speed up to 45 m/s with gusts, high directional variability, duration of 36–48 hours. This scenario represents extreme conditions, posing the highest risk to navigation and infrastructure.

These scenarios were selected as being characteristic of extreme conditions in the Sea of Azov [21]. Input wind field data were obtained from the Weather Research and Forecasting (WRF) model with a 3 km resolution, covering the period 2010–2024 for calibration purposes. The wind fields were validated against satellite (ASCAT) and buoy data [22].

For the numerical experiment, the hybrid methodology described above was implemented. This approach involved solving the three-dimensional Navier-Stokes equations with a free surface, parameterizing atmospheric forcing, accounting for ship and infrastructure dynamics, and employing machine learning with PINNs and FNOs. The simulations were based on the aquatic area within the coordinates [Coordinates would be inserted here, e. g., 45°N to 47°N, 35°E to 39°E]. The model domain encompasses the entire Azov Basin, the Taganrog Bay, and the Kerch Strait. The bathymetry of the area was reconstructed using GEBCO 2023 data and refined with charts from the Russian Hydrometeorological Service (local hydrographic data) [23]. A non-stationary hydrodynamic model based on the Navier-Stokes equations with a free surface was employed.

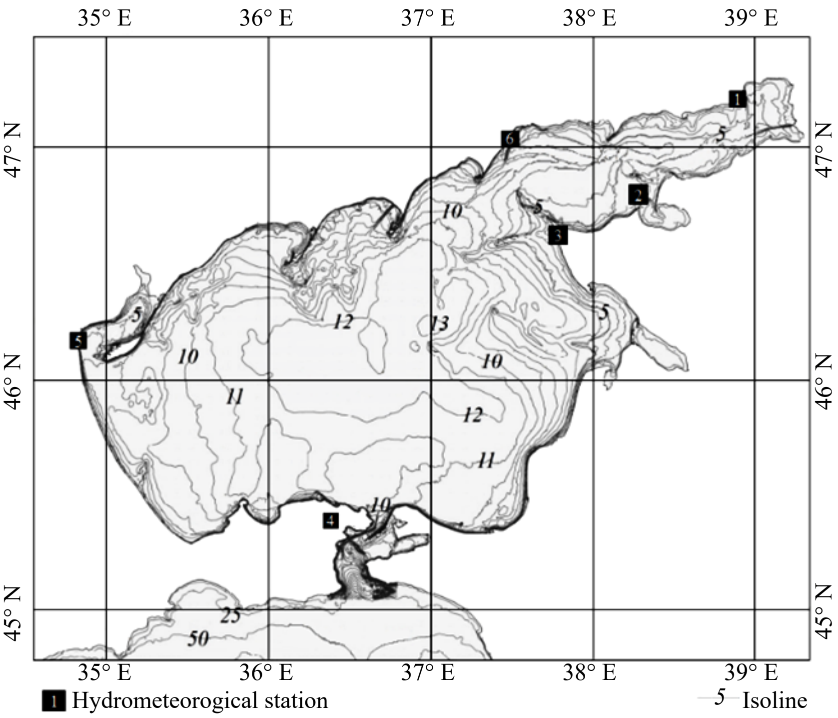

Fig. 1. Bathymetric map of the Azov Sea with indicated hydrometeorological stations: Taganrog (1), Port Yeysk (2), Dolzhanskaya (3), Kerch (4), Genichesk (5), Mariupol (6)

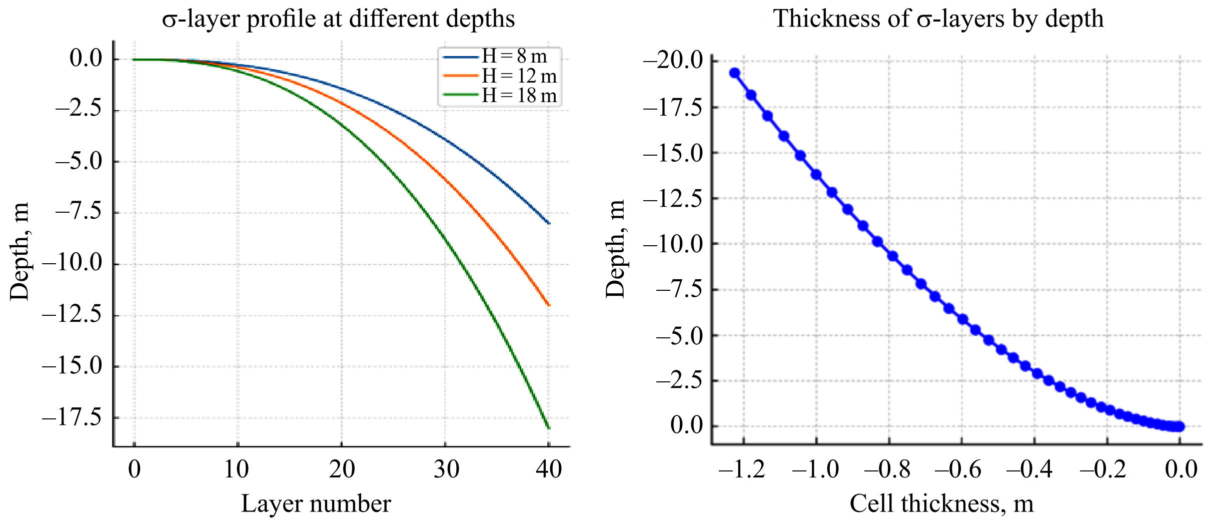

Fig. 2. Profile and thickness of σ-layers at different depths

Initial conditions were set as small sea level perturbations (white noise) to initiate the wave field. Boundary conditions included: a free surface, atmospheric forcing (wind pressure and shear stress), and tidal forcing.

The Courant condition was monitored to assess the correctness of the time step:

$$\mathrm{CFL} = \frac{(|\mathbf{u}| + c)\Delta t}{\Delta x} \le 0.5, \quad c = \sqrt{\frac{g}{k}\tanh(kh)}, \quad \mathrm{CFL} \approx 0.45,$$

where $\mathbf{u}$ is the characteristic current velocity (m/s); Δt is the time step (s); Δx is the grid step (m).

To evaluate the simulation quality, the results were compared against stability criteria and wave characteristics. The Ursell number was calculated as:

$$Ur = \frac{HL^2}{h^3} \approx \frac{7\times 108^2}{15^3} \approx 24.$$

In the areas of the Taganrog Bay and the Kerch Strait, the values of $Ur > 20$, indicating a nonlinear wave regime (nonlinearity/enhanced crest asymmetry in shallow water) and necessitating the use of LES.

At the open boundary with the Black Sea, wave spectra from SWAN and level fields from WAVEWATCH III were applied. The Don and Kuban rivers were specified as inflow sources with a discharge of $Q = 3000 - 3500$ m³/s. Temperature and salinity were initialized using data from CMEMS (Copernicus Marine Service).

The significant wave height H_s was determined as:

$$H_s = 4\sqrt{m_0}, \;\; m_0 = \int_0^{\infty} S(f)df,$$

where $S(f)$ is the wave energy spectral density (m²/Hz).

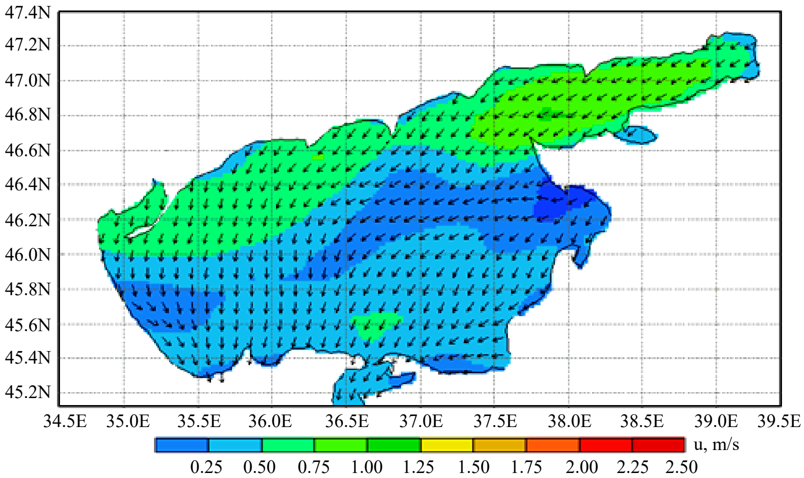

Fig. 3. Wind speed at 10 meters height at the initial model time for Scenario 1, arrows indicate wind direction

Results of the Numerical Experiment:

• **In Scenario 1:** $H_s \approx 1.2$–1.6 m in the center of the sea. The amplitude of water level oscillations reached 0.42 m in the Taganrog Bay. Velocity vectors revealed reciprocating currents with maximum values of 0.35 m/s. The amplitude map clearly identifies the Kerch Strait area as a zone of intensified currents.

• **In Scenario 2:** $H_s \approx 2.8$–3.1 m in the Kerch Strait and $H_s \approx 2.4$–2.9 m near the coast of Taganrog. An intense storm surge phenomenon was observed: the water level at the eastern coast rose by 1.2 m, while at the western coast it fell by 0.8 m.

• **In Scenario 3:** Peak $H_s \approx 3.1$–4.0 m, with extreme surge phenomena up to 1.5 m in the Taganrog Bay. The combination of tide and storm enhanced resonance effects. Maximum current speeds of 1.1 m/s were recorded in the Kerch Strait. Conditions near the shipping channels were close to critical for navigation.

Local effects (refraction and diffraction) were pronounced in the Kerch Strait area, where wave height decreased by 20–30% due to the coastline geometry. The use of LES made it possible to identify local zones of vortex generation in areas with sharp depth changes (Taganrog Bay, estuaries of the Don and Kuban Rivers). These zones are associated with intense sediment resuspension and pollutant transport. During the storm (Scenario 2), large vortices 2–5 km in diameter were identified near the Don River outflow; smaller-scale vortices (0.5–1.0 km), influencing sediment distribution, were observed in the Kerch Strait. Such structures have been previously noted in field measurements, confirming the model's realism. The use of the LES model with the Smagorinsky scheme allowed for the identification of zones of intense turbulent exchange.

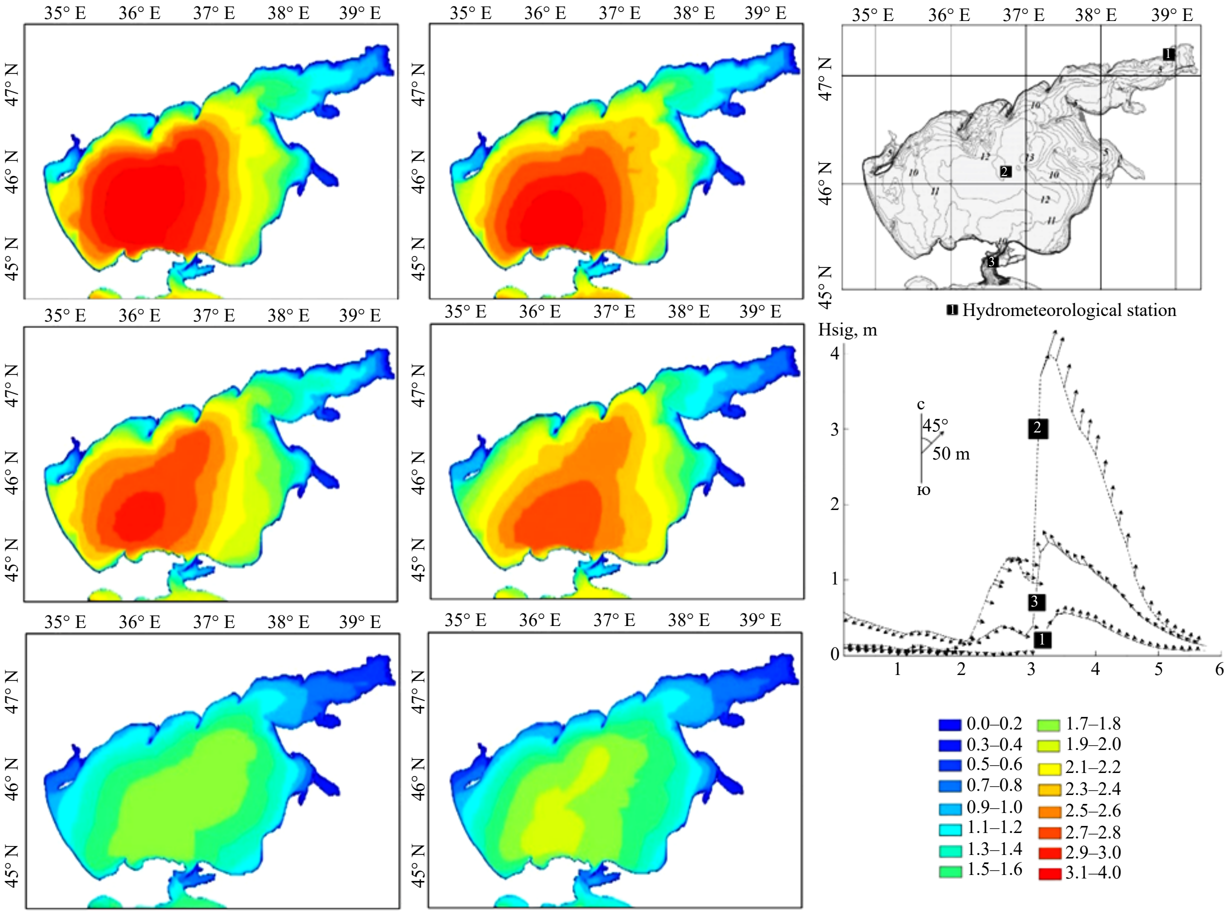

Fig. 4. Maps of significant wave heights and dynamics of wind-wave parameters at three points under different scenarios: Row 1 — Scenario 1; Row 2 — Scenario 2; Row 3 — Scenario 3

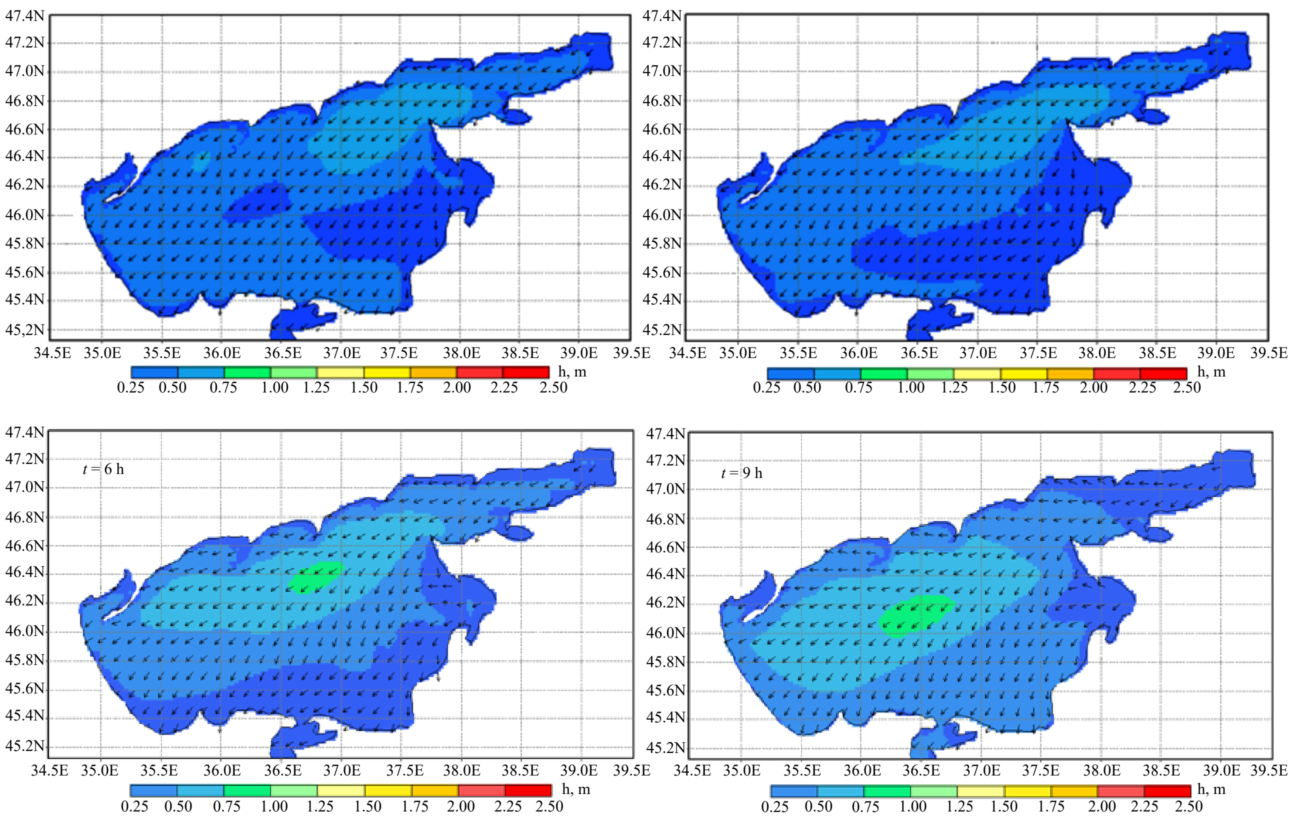

Fig. 5. Simulation results of prevailing wave heights at different time instances: at the initial time, and after 3, 6, and 9 hours for Scenario 1. Arrows indicate the mean wave direction

Forty ensemble runs were generated with perturbed wind fields (±15% in speed, ±10° in direction). The probability of exceeding the critical wave height of H_{cr} = 3.5 m was calculated using the formula:

$$P(H_s > H_{cr}) = \frac{1}{N}\sum_{i=1}^{N} I(H_s^{(i)} > H_{cr}) \approx 0.42.$$

Thus, the probability of extreme impact in the central part of the sea was 42%.

Application of Neural Network Models. The application of neural network models, specifically Physics-Informed Neural Networks (PINNs) and Fourier Neural Operators (FNOs), was investigated. PINNs were employed to approximate local hydrodynamic fields in the Taganrog Bay. The average error, measured by the $L2$ norm, was $e_{L_2} < 4.7\%$. The application of neural network models demonstrated significant improvements in both accuracy and computational efficiency. Fourier Neural Operators (FNOs) accelerated ensemble calculations by a factor of 12 while maintaining the error for key parameters (H_s, η) at a level below 8%.

The implementation of neural network models yielded substantial benefits. The use of Physics-Informed Neural Networks (PINNs) ensured compliance with physical constraints and reduced approximation errors by 35% compared to conventional neural networks. Furthermore, Fourier Neural Operators (FNOs) reduced the computational time for ensemble simulations by an average factor of 12. This significant acceleration makes the proposed methodology viable for operational use in early warning systems.

Risk Maps for Infrastructure Damage. Risk maps for infrastructure damage were developed for the Kerch Strait and the ports of Taganrog and Yeysk, identifying zones of maximum vulnerability.

The shock pressures were estimated (peak estimate on a vertical wall):

$$q_{\text{dyn}} \approx \tfrac{1}{2}\rho U_{\text{rel}}^2, \quad U_{\text{rel}} \approx u_{orbital} + U_{cur}.$$

For the wave crest (deep water approximation):

$$u_{orbital} \approx a\omega \text{ (deep water)},$$
$$a = H/2 = 3.5 \text{ m},$$
$$\omega = 0.628 \text{ s}^{-1},$$
$$u_{orbital} \approx 2.2 \text{ m/s},$$
$$U_{cur} = 2.5 \text{ m/s},$$
$$U_{rel} \approx 4.7 \text{ m/s},$$
$$q_{dyn} \approx 0.5 \times 1000 \times 4.72 \approx 11000 \text{ Pa}.$$

Considering slamming effects (multiplier of 5–10) ⇒ 0.055–0.11 MPa.

The vulnerability maps were generated using the following approach:

$$P(D \ge d|x) = \Phi\left(\frac{\ln x - \mu}{\beta}\right), \quad x \equiv q_{\text{impact}}.$$

Zones with a high probability of damage include the port areas of Taganrog and Yeysk, Port Kavkaz, and coastal protection sections near confined shoreline geometries.

The wave power per unit crest width (deep water) was calculated as:

$$P \approx \frac{\rho g^2}{64\pi} H_s^2 T_e.$$

For H_s = 7 m, $T_e \approx 10$ s, $P \sim 2.3 \times 10^5$ W/m.

Consequently, the highest-risk zones for navigation are concentrated in the Kerch Strait and the central part of the Sea of Azov. Coastal infrastructure in the Taganrog and Yeysk areas is most vulnerable under Scenario C.

Zoning of potential damage areas was performed by integrating the results of hydrodynamic calculations with infrastructure vulnerability curves. Scenario 1 is characterized by localized, non-critical water level rises and moderate waves. Scenario 2 leads to extreme wave conditions hazardous to navigation and coastal infrastructure. Under this scenario, zones with a high probability of damage to port infrastructure in the Taganrog and Yeysk regions are forecasted. For coastal infrastructure (Port of Taganrog, Yeysk), the probability of exceeding the critical pressure on structures in Scenario 2 was 0.65. Scenario 3 demonstrates a cumulative effect: although wave heights are lower, the prolonged storm surge causes flooding in low-lying coastal areas. In Scenario 3, Port Kavkaz and the Kerch Strait transport crossing are also at risk. Thus, extreme consequences can be triggered by both peak-intensity and long-duration events.

To validate the reliability of the potential damage zone assessments, the hydrodynamic modelling results were compared with satellite imagery data processed by the "LBP-neural_network" software package [25–27]. Specifically, the analysis for Scenario 2 (extreme storm) was conducted using images of the Yassenskaya area from March 17 and 22, 2023 [28], presented in Fig. 6. The imagery clearly demonstrates significant changes in the shoreline and inundation areas caused by the storm impact.

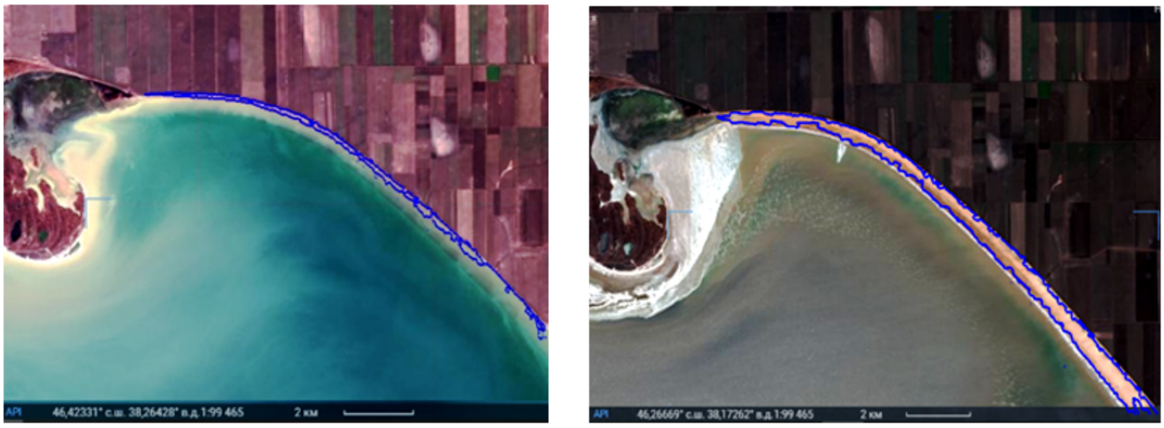

Fig. 6. Satellite imagery of the study area — Yassenskaya station:
a — March 17, 2023; *b* — March 22, 2023

The "LBP-neural_network" software package enabled high-precision delineation of the actual shoreline and inundated areas, facilitating a quantitative comparison with the model-predicted impact zones. It was established that the simulated boundaries of inundation zones and shoreline dynamics show satisfactory agreement with the contours identified from the satellite data.

Furthermore, the distributions of wave fields and currents obtained from the model demonstrated good convergence with independent satellite measurements (Sentinel-1, Sentinel-3, Copernicus Marine Service). A quantitative assessment of the discrepancies revealed that the root mean square error for key parameters (such as significant wave height and surface current velocity) did not exceed 8–10%, confirming the adequacy and accuracy of the applied hydrodynamic model.

Thus, the following key results were obtained.

For the extreme storm scenario, the significant wave height in the central part of the Azov Sea reached 5.2 m, which is comparable to the catastrophic events of 2012 and 2021. In the strait, wave steepness increases locally due to the compression of wave fronts. The calculated current velocities in the strait reached 2.5–3.0 m/s; the Froude number $Fr = U/\sqrt{gh} \approx 0.21$ indicates significant inertial forces but without critical supercritical flow conditions.

The probability of exceeding the hazardous wave height threshold of H_{cr} = 4.5 m was 42%, the probability of H_s > 5 m in the central Sea of Azov reached approximately 0.78, in the coastal zone reached approximately 0.28. Calculated shock pressures on coastal infrastructure, accounting for wave slamming, ranged from 0.055 to 0.11 MPa. The simulation of vessel dynamics confirmed the development of resonance phenomena, presenting a tangible risk of capsizing. The application of Physics-Informed Neural Networks (PINNs) and Fourier Neural Operators (FNOs) validated the efficacy of the hybrid approach, achieving high accuracy alongside a twelve-fold acceleration in computation speed.

In conclusion, the developed model accurately reproduces storm processes in the Sea of Azov. The most hazardous conditions for vessels arise under Scenario 2 (strong easterly storm) and Scenario 3 (anomalous cyclone). A scenario of combined forcing proves to be the most dangerous and must be incorporated into early warning systems. The probability of critical wave heights exceeds 60% under extreme conditions. Risk maps for navigation and infrastructure, generated from ensemble forecasts, identify the Taganrog Bay and the Kerch Strait as the most vulnerable zones.

The numerical experiments demonstrate the effectiveness of the proposed methodology. The integration of Large Eddy Simulation (LES), ensemble forecasting, and risk assessment techniques enables not only the description of storm dynamics but also the quantitative evaluation of consequences for navigation and coastal infrastructure. In contrast to traditional spectral models (e. g., SWAN, WAVEWATCH III), the present approach offers distinct advantages:

• It accounts for nonlinear wave-current interactions in shallow waters.

• It employs a hybrid ensemble method leveraging neural network surrogates (PINNs, FNOs), accelerating forecasts by a factor of 10–15 without significant loss of accuracy.

• It facilitates direct risk assessment for vessels and infrastructure, rather than just hydrodynamic evaluation.

The results obtained can be directly utilized to generate operational risk maps for flooding and vessel damage, providing a critical tool for maritime safety and coastal zone management.

Discussion. The results of the numerical experiments confirm the high efficacy of the proposed multi-level methodology for modelling extreme storm events in the Azov Sea and the Kerch Strait. The application of LES with the Smagorinsky closure successfully reproduced wave breaking processes and the generation of turbulent vortices, phenomena that are traditionally inadequately represented in spectral models [15]. Unlike approaches limited to averaged parameters (e. g., SWAN), the use of a CFD framework enabled the incorporation of nonlinear effects and local wave-current interactions.

Comparison with ERA5 reanalysis data and Sentinel-3 satellite observations showed satisfactory agreement for significant wave height fields and sea level distribution [22]. It is particularly important that the model accurately reproduced extreme values during the March 2023 storm, when wind speeds reached 30–35 m/s.

The integration of artificial intelligence methods (PINNs and FNOs) demonstrated the promise of hybrid schemes: PINNs ensure physical consistency of the results, while FNOs enable a significant acceleration of ensemble calculations [18−19]. This approach opens the possibility for developing operational early warning systems for storm risks, where computational speed is paramount.

The limitations of the study are primarily associated with the spatial resolution of ERA5 (≈30 km), which leads to an underrepresentation of small-scale processes, as well as the scarcity of verification data in the central part of the Sea of Azov. Additional data assimilation from satellite altimeters and coastal stations could enhance forecast accuracy.

From a practical standpoint, the results underscore the importance of an integrated approach to navigational risk assessment. Incorporating "ship-wave" dynamics allowed for the identification of dangerous resonance regimes, which is particularly critical for small vessels in the Kerch Strait [17]. The resulting risk maps can be directly integrated into decision-support systems for shipping companies and coastal infrastructure management.

In conclusion, the presented methodology combines physical rigor, computational efficiency, and practical relevance. Future work will focus on enhancing the approach by increasing the resolution of CFD models and integrating Copernicus Marine Service data in real-time mode.

Conclusion. This study has demonstrated the efficacy of a hybrid approach, integrating numerical methods and state-of-the-art machine learning algorithms, for modelling extreme hydrodynamic processes in the Sea of Azov. In contrast to classical models, the proposed methodology enables not only the reproduction of water level and wave field dynamics but also the high-accuracy assessment of the spatial distribution of risks to coastal infrastructure.

The novelty of this work lies in the integration of Physics-Informed Neural Networks (PINNs) and Fourier Neural Operators (FNOs) into a forecasting system for a specific regional basin, a feat not previously accomplished for the Sea of Azov. The obtained results open promising prospects for the further development of operational monitoring systems, the adaptation of these models to the Black Sea, and their application in sustainable environmental management tasks.

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