



Efficient reconstruction of nearshore sea state and bathymetry from marine radar images

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ABSTRACT

In-situ monitoring of waves is usually limited to provide spatio-temporal information. However, remote sensing tools (RSTs) can be complementary to eliminate this limitation. In this study, a novel framework, Lightweight Image Assimilation (LMS), has been developed for RSTs which is capable to gather information on hydro-morphodynamics by utilizing Radon transformation, advanced signal processing methods, and histogramming to eliminate outliers. LMS was tested at our study site where two different RSTs were deployed: an X-Band Radar and a video monitoring system. LMS has been benchmarked with field observations and alternative processing tools by utilizing radar images, which are collected every hour with 0.5 Hz frequency. The statistical measurements showed that LMS was capable to reconstruct the evolution of wave characteristics (e.g. significant wave height, $r^2 = 0.79$, $RMSE = 0.21$ m) and the bathymetry ($r^2 = 0.70$, $RMSE = 0.55$ m). LMS outperformed alternative tools despite less computational demand. However, a systematic overestimation was observed for all methods and the performance was affected by cross-sea altered signals where LMS allowed to diagnose the source of alteration. The wave characteristics derived from the framework were used to force the phase-resolving model to investigate coastal inundation and compare with empirical formulations. Consequently, the framework can be used as a comprehensive tool to investigate hydro-morphodynamic processes, their impacts on the coastal regions, and to have an insight on the coastal resilience.

1. Introduction

Nearshore is a region bounded by the shore and the inner-shelf. Decrement in water depth towards the shoreline may result in overlapping of surface and bottom boundary layers (Lentz, 1995), eventually, complex processes are triggered due to many interactions (e.g. wave-wave, wave-seabed, wave-current). This complexity is increased when there are additional presences such as coastal structures and estuaries (Brocchini, 2020). Therefore, it brings the necessity of measurement of these processes to investigate them to better understand their mechanisms and for assessment of the safety of our coastal regions.

The measurements can be done by in-situ devices or remote sensing tools (RSTs). In-situ measurements are usually collected from a single point, which can limit the spatial information. The absence of spatio-temporal characteristics may prevent us to resolve complete dynamics. However, this limitation could be eliminated by combining with RSTs with in-situ measurements. Lippmann and Holman (1989) demonstrated that video recordings from a shore-fixed camera can be used to study morphodynamic processes, which was the basis of Argus-like monitoring systems. The use of marine radars to study hydro-morphodynamic processes was also well established (Young et al., 1985; Bell, 1999).

Thoroughly generated processing tools are essential to properly analyse RST data. Following technological advancements in image and signal processing, computational capabilities have increased significantly. Mode decomposition techniques allowed us to obtain more information on wave characteristics from optical images to be used in depth inversion methods by exploiting the dispersion equation (Holman et al., 2013; Simarro et al., 2019; Gawehn et al., 2021). The application of advanced techniques on radar images revealed that marine radars are efficient remote sensors for utilization since they have relatively large coverage and are more resistant to weather conditions than optics (Rutten et al., 2016; Honegger et al., 2019, 2020; Atkinson et al., 2021). They can also be coupled with synthetic models, analytical methods, in-situ measurements, and numerical models due to their data collection mechanism (Nieto Borge et al., 2004; Greenwood et al., 2018; Simpson et al., 2020; Szczyrba et al., 2024; Humam and Takewaka, 2025).

The adoption of pattern recognition methods, such as Radon transformation (RT), resulted in better characterizing the wave propagation dynamics and better performing algorithms. Almar et al. (2014) showed that RT can be effectively utilized to estimate individual wave celerities and distinguish incoming and outgoing waves. It was proven

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that the variance of Radon sinogram can be used to determine the wave direction (Bergsma et al., 2019; Holman and Bergsma, 2021). Furthermore, O'Dea et al. (2025) demonstrated that the directional spectra can be evaluated by applying FFT to Radon sinogram. The potential of Continuous Wavelet Transformation (CWT) was proven to investigate the evolution of wave characteristics, thanks to its ability to jointly provide time-frequency, or space-wavenumber, information (Lilly and Olhede, 2008). Wu et al. (2011) were the first presenting the application of 2D CWT to estimate wavenumber spectrum from radar images. Then, this approach was further developed to evaluate the bathymetry (Chernyshov et al., 2020).

In general, based on the final products, three main types of approach exist. The first type includes tools focusing on derivation of bathymetry but not clearly presenting spatio-temporal characteristics of wave propagation (Holman et al., 2013; Simarro et al., 2019). The second type focuses on wave propagation dynamics, especially free surface elevation, but the bathymetry derivation is not considered (Greenwood et al., 2018; Simpson et al., 2020). The last group is usually provided as a commercial product which can give complete information on hydro-morphodynamics by compromising on computational efficiency (Serafino et al., 2012). Multidimensional signal processing (e.g., 3D FFT, 2D CWT) is involved in these tools. This may require greater computational resources and longer sampling durations to achieve better frequency resolution.

In this study, we have developed a framework to resolve spatial evolution of wave refraction and celerity by utilizing RT. Refracted sampling of data allowed us to use 1D CWT to reconstruct the wavenumber evolution. FFT-free, histogram-based method is adopted to determine the peak frequency accurately even from short samplings, and estimate the bathymetry by inverting the supereminent dispersion equation:

$$c = \frac{gT}{2\pi} \tanh(kh) \quad (1)$$

where c is wave celerity, g is the Earth's gravitational acceleration, T is wave period, k is wavenumber, and h is still water depth. Moreover, the significant wave height is predicted by a relatively simple regression model based on raw signals and estimated wavelength to provide complete wave characteristics.

LMS acquisition only focuses on the peak wave parameters instead of modal analyses and collection of multiple frequency–wavenumber pairs. Combining with the regression model, LMS can provide complete peak wave characteristics along with bathymetry in an efficient way owing to dimensional reduction in space. To demonstrate the usefulness of this approach, LMS-derived wave characteristics have been fed to FUNWAVE-TVD (FW), a phase-resolving Boussinesq model (Shi et al., 2012), to conduct inundation analyses similar to recent works, focused on the synergic use of numerical modelling and algorithms used for bathymetry and wave reconstruction from radar signals, though not based on real world field data (Postacchini et al., 2023). It will allow us to better understand the wave propagation dynamics, and its impacts on the coast.

The content of this article is structured as follows: Section 2 is reserved for the study site characteristics and details of deployed instrumentations. The image assimilation framework is demonstrated step by step in Section 3. The phase-resolving numerical model setup and empirical inundation models are explained in Section 4. The results are illustrated in Section 5 and Section 6 is reserved for discussion and description of limitations. Sections 7 and 8 contain the tool application to coastal inundation analyses and conclusions, accompanied with forewords, respectively.

2. Study site

The study site is Senigallia, a maritime city at the central Adriatic coast indicated by an orange rectangle in Fig. 1A. The city accommodates the Misa River Estuary (MRE), a small harbour and sandy beaches. The northern coast is protected by emerged wavebreakers

Table 1

The characteristics of RSTs deployed at MRE.

Instrument	Sampling rate	Sampling duration	Resolution	Coverage
XBR	0.5 Hz	125 s	7.5 m	4.5 km
SGS	2 Hz	10 min	1 m	500–1000 m

whereas the southern part is unprotected. The composition of beach sediments is a mixture of fine and medium sand ($D_{50} = 0.125\text{--}0.5$ mm). The slope of swash-surf zone is ranged between 1:30–1:40 whereas it gets as small as 1:200 at intermediate depths ($h > 3$ m). The bathymetry data published by Marine Science Institute (ISMAR-CNR) further supports that the intermediate depths extend several kilometres from the shoreline (Fig. 1B). Most of the energy is brought by waves coming from NNE and ESE (Postacchini et al., 2017). The MRE has a microtidal regime where the range is 0.3–0.5 m, and more prone to surge-dominant inundation (Baldoni et al., 2024), especially vulnerable to compound flooding (river + storm surge) due to low-lying terrain. Prominent seasonal variabilities (Brocchini et al., 2017), devastating natural hazards (Tartaglione, 2025), and presence of complex physical processes (Melito et al., 2020) brought the necessity of continuous monitoring of the site. Therefore, a multi-purpose station (MEDA), an X-Band Marine Radar (XBR) and shore-fixed multi-camera system (SGS) were deployed (Fig. 1, B). The main characteristics of each RSTs are summarized in Table 1. MEDA measurements of wave characteristics were used for the validation of the model. In the present work, only XBR was used to demonstrate the capabilities of LMS.

3. Image assimilation

LMS consists of three conceptual phases of analyses, each responding to a logical requirement, to retrieve the wave direction, wave kinematics, peak wave parameters and bathymetry. The adopted algorithm for each corresponding output and intended use are illustrated as a flowchart in Fig. 2. The first phase is to capture the wave refraction by applying RT and create sampling rays that follow the wave propagation. Therefore, the spatial dimension can be reduced to the wave path only. In the second phase, the RT is further used to examine 2D timestacks obtained from the mentioned rays to resolve the celerity evolution. In both cases, the RT is applied to an image in the x, y plane based on:

$$R(x_p, \theta) = \int_{-\infty}^{\infty} f(x_p \cos \theta - y_p \sin \theta, x_p \sin \theta + y_p \cos \theta) dy_p \quad (2)$$

where θ is the rotation angle of the image with respect to x , x_p and y_p represent the rotated axes, and $R(x_p, \theta)$ is the integration of the rotated image along y_p , respectively. The rotation limits are set to $0.25\text{--}180^\circ$ with a 0.25° discretization. Eq. (2) reveals that R retains explicit spatial dependence, allowing for direct characterization of the local wave-crest geometry. Although local FFT-based methods can account for shoaling and refraction (Ludeno et al., 2018) by applying a sliding-window analysis, their performance relies on the assumption that the wave properties vary slowly enough within each subarea for a local spectral representation to remain valid. The proposed approach directly extracts the orientation of wave crests, providing a complementary strategy that is particularly suitable when wave fronts exhibit significant curvature or rapid spatial variations.

The continuously varying aspect of propagating waves brings in the necessity of gathering coupled information in the space-wavenumber domain. Therefore, following the second phase, the evolution of wavenumbers is determined by conducting CWT analyses to spatially-varying signals obtained by refracted sampling by adopting the Generalized Analytic Morse Wavelet, which can provide an optimal space-wavenumber localization (Lilly and Olhede, 2008). The CWT coefficients with a chosen wavelet (ψ_X) can be evaluated by:

$$W(A, X_p) = \frac{1}{A} \int_{-\infty}^{\infty} f(X) \psi^* \left(\frac{X - X_p}{A} \right) dX \quad (3)$$

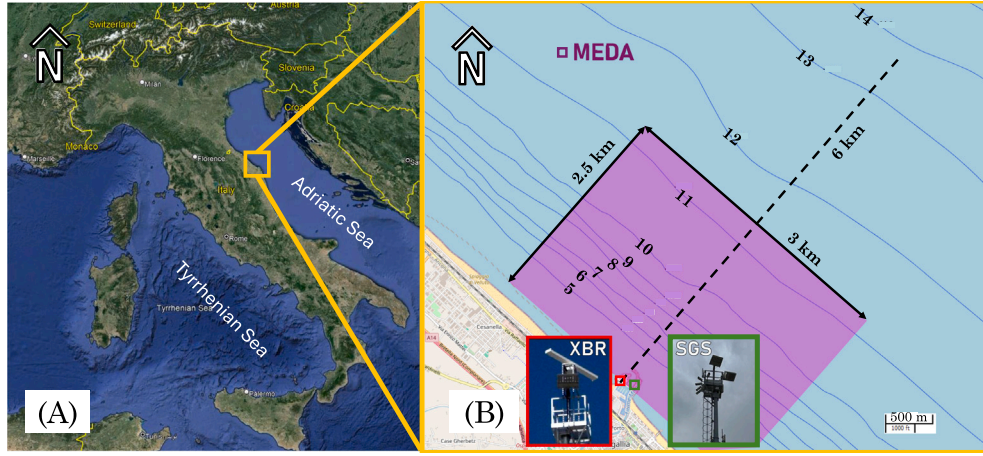


Fig. 1. A: The geographic location of Senigallia. B: The bathymetry contours of the study site accompanied with the positions of the XBR, SGS and MEDA station, which are indicated by red, green and purple square markers, respectively. The magenta area represents the XBR analysis domain and dashed line indicates the 6 km offshore distance from the XBR location, respectively.

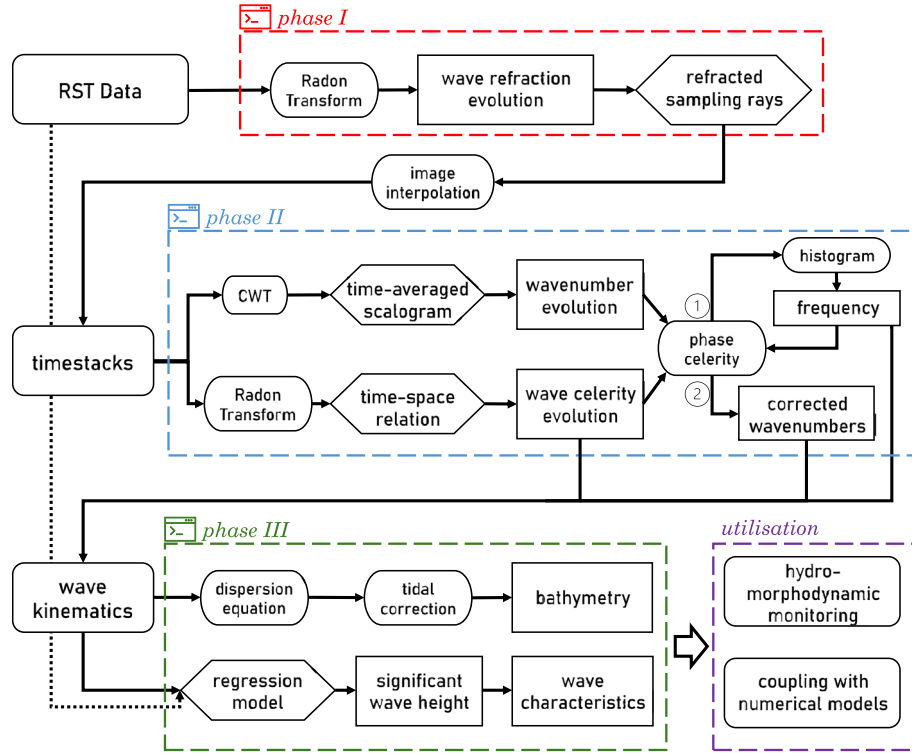


Fig. 2. The flowchart of the proposed image assimilation framework.

where A is the scale parameter, X_p is the spatial position, and ψ^* is the complex conjugate of the chosen wavelet. The explicitly derived celerity and wavenumbers are substituted to the phase celerity formula to estimate the peak frequency. Then, the wavenumbers are corrected to be consistent with the peak frequency and celerity. In the last phase, the bathymetry is reconstructed by solving Eq. (1), with derived wave kinematics and the significant wave height is estimated with a simple regression model.

3.1. Wave refraction

Determination of the correct wave direction is important to retrieve appropriate wavenumbers and wave celerity. The change in propagation direction along the cross-shore direction can be evaluated by

utilizing RT similar to previous applications (Bergsma et al., 2019; Holman and Bergsma, 2021). However, the main aim of this approach is retrieval of the evolution of the wave direction by applying RT using sliding windows. Parametric analyses revealed that the optimum window size was 40 pixels, which can provide at least two wave crests in a single window at the offshore of our study site, and the sliding amount was 20 pixels to properly capture the refracted waves.

The RT is applied to the mean-removed signals from each window to obtain $R(x_p, \theta)$, and the variance along θ is evaluated. The angle corresponding to the maximum variance is extracted and the procedure is repeated for every window. Because noise content can affect the reliability of estimations, a histogram-based approach is adopted to eliminate the outliers. The method is realized by computing the

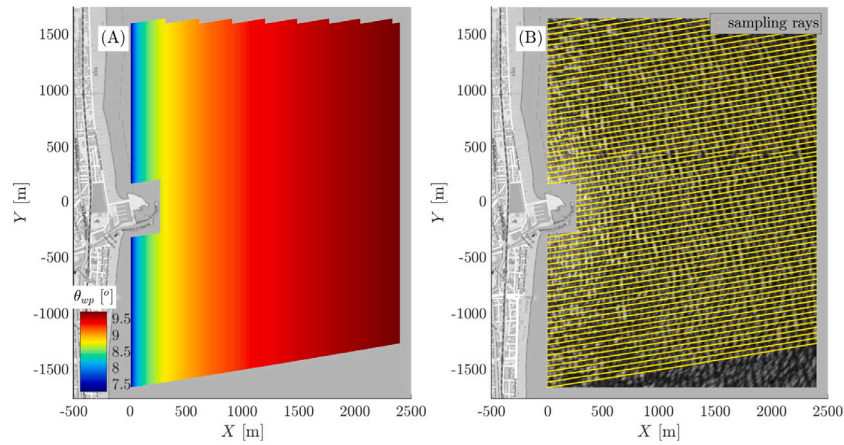


Fig. 3. A: The wave refraction obtained by radon analyses. B: Sampling rays over a XBR snapshot which can account for refraction.

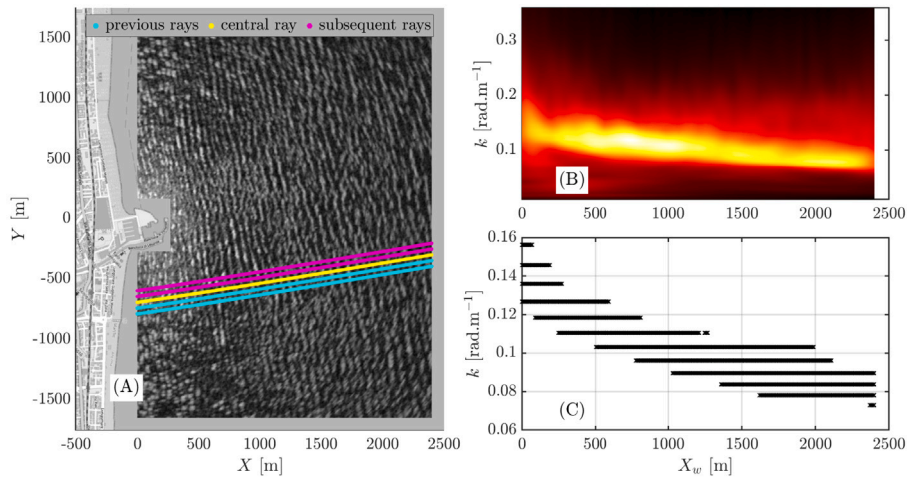


Fig. 4. A: Central, two previous and two subsequent sampling rays illustrated on the XBR snapshot. B: Averaged scalogram corresponding to these rays. C: The variation of k obtained from the scalogram along the X_w for all sampling rays.

residuals from the mean as

$$\epsilon = \theta - \bar{\theta} \quad (4)$$

where θ is the angles derived for all windows and $\bar{\theta}$ is the mean angle. The residuals are histogrammed using the [Freedman and Diaconis \(1981\)](#) binning method where the bin width is defined as

$$W_b = 2IQRn^{-1/3} \quad (5)$$

where IQR denotes the interquartile range of residuals and n is the sample size. It is assumed that the reliable results are located within the ranges where the histogram gives the maximum count number, corresponding to ϵ' . Then, the angles that satisfy the condition

$$|\epsilon + \epsilon'| > 2W_b \quad (6)$$

are classified as outliers.

After eliminating outliers, a power-law function is fitted to data to construct the relation between the angles and the cross-shore distance (θ , X) as elaborated in Section Radon-based Pattern Extraction Method (Fig. 3A). Eventually, the sampling rays can be created by accounting for the wave refraction. Depending on the desired spatial resolution or sampling number in the Y direction, the integration constant (y_0 , Eq. (A.3)) can be adjusted accordingly. This coefficient was arranged to provide nearly 40 m resolution in the alongshore direction, which made 70 sampling rays in total (Fig. 3B). Considering the morphological characteristics of the study site, this discretization yielded fairly good results. Afterwards, the raw images are interpolated to sampling rays.

3.2. Wave kinematics

The spatial variation of wavenumbers is determined by applying CWT to time-stacks of each ray and averaged over the sampling period (63 scans in this case). Additional averaging is applied by including neighbour rays which can be provided by user (e.g. [2, 2] window includes two previous and two subsequent rays, Fig. 4A).

The main motivation of this approach is to prevent the impacts of persistent local disturbances in the signal and ensure consistency between adjacent rays. The averaging of the scalogram promotes the dominant wavenumbers (Fig. 4B). The wavenumber corresponding to the maximum scalogram at each position along wave path, X_w , is extracted. If there are multiple wavenumbers for each position, all of them are extracted and outliers are eliminated by histogramming. Finally, wavenumber envelope can be obtained along X_w (Fig. 4C). The celerity is obtained by analysing individual time-stacks corresponding to each sampling ray. When this time-stack is investigated, the prominent patterns can be recognized due to motion of wave crests (Fig. 5A). Similar to the evaluation of the refraction, RT is used to reconstruct the time-space (t , X_w) relation of the wave motion. The sliding window width is set to 40 pixels similar to the refraction estimation, but the sliding amount is reduced to 5 pixels to accurately capture the celerity evolution.

XBR coverage extends from shallow to intermediate water (Fig. 1B). Therefore, two functions are used for fitting: a power-law function to represent shallow water celerity and a hyperbolic tangent function to

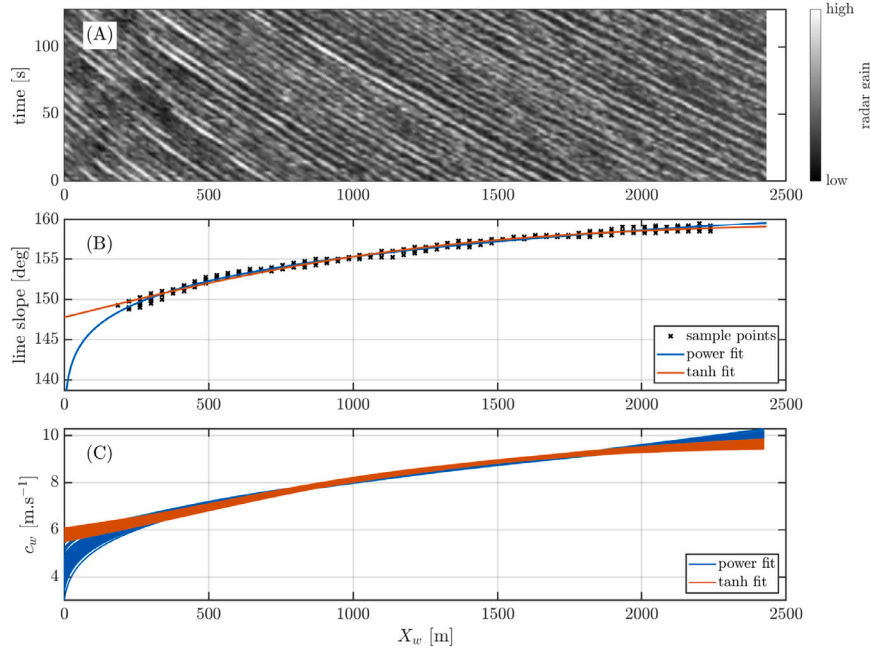


Fig. 5. A: The time-stack obtained from the central ray (Fig. 4, A). B: Two fitted curves for the sample points obtained from the central, previous and subsequent rays (Fig. 4, A). C: Evaluated wave celerity for two fittings and for whole rays.

represent the wave celerity over intermediate depths. For each ray, two curves were fitted following Radon-based pattern extraction method by including neighbour rays similar to the derivation of wavenumbers (Fig. 5B). Then, the fitted curves were substituted to Eq. (A.3) to obtain $t-X_w$ pairs. Since time-space relation was derived, the wave celerity (c_w) can be obtained by differentiating in time ($c_w = \frac{\partial X_w}{\partial t}$) as demonstrated in Fig. 5C. The time-space reconstruction allows one to estimate the propagation direction. For instance, based on the axis convention, negative slopes (line slope > 90 deg) indicate a shoreward directed celerity vector. However, absolute values are used in fitting sequence to keep consistency.

Since we derived wave celerity and wavenumber evolution, the frequency matrix can be approximated by arranging phase celerity formula: $\mathbf{f} = \frac{c_w \mathbf{k}}{2\pi}$. The c_w is based on *tanh* since intermediate depths cover a larger area than shallow depths (Fig. 1B). Due to the sparsity of wavenumbers, frequency matrix is not homogeneous as illustrated in Fig. 6A. Therefore, the dominant frequency of the wave propagation is obtained from the histogram as follows: The histogram results are converted to the cumulative density function (CDF) and smoothed (Fig. 6B). Then, the smoothed CDF is converted to the probability density function (PDF) and the frequency corresponding to the maximum PDF is chosen as the peak frequency (Fig. 6C).

The sparsity of wavenumbers is eliminated by substituting the peak frequency, f_p , into the phase celerity formula to derive corrected wavenumbers: $\mathbf{k}_{cor} = 2\pi f_p / c_w$. Since two separate fittings are used (*power* and *tanh*), two separate wavenumber matrices are obtained. Therefore, moving from onshore to offshore, the first index that minimizes the difference between the phase celerities is chosen as the transition point between the fittings. Consequently, the shoreward section is modelled using a *power* fitting, while the seaward section follows a *tanh* fitting (Fig. 5C).

3.3. Bathymetry and wave height

This part of the framework is designed to estimate the water depth by solving Eq. (1), and significant wave height, H_s , with a simple regression model. All necessary variables were evaluated to solve the equation. However, a small correction is applied to the celerity to decrease the error arose from wavenumber envelope ($\mathbf{k}$). The primary

source of error is the derivation of celerity from crest tracking. Specifically, crest celerity can exceed phase celerity as nonlinearity increases (Tissier et al., 2011; Postacchini and Brocchini, 2014). The correction applies as:

$$\mathbf{c}_0 = \frac{2\pi f_p}{\mathbf{k}} \rightarrow \Delta \mathbf{c} = \mathbf{c}_0 - \mathbf{c}_w \rightarrow \mathbf{c}_{cor} = \mathbf{c}_w + \left(\overline{\Delta c} \right)_{dom} \quad (7)$$

where $\mathbf{c}_{cor}$ is the corrected celerity, and $\left(\overline{\Delta c} \right)_{dom}$ is the dominant difference between $\mathbf{c}_0$ and $\mathbf{c}_w$ obtained by histogramming (same as in Section 3.1). Afterwards, the dispersion equation (Eq. (1)) can be solved in the following form to derive the initial water depth, $\mathbf{h}_{ini}$:

$$\mathbf{h}_{ini} = \frac{\left(\tanh \left(\frac{\mathbf{c}_{cor}}{T_p} \right) \right)^{-1} \left(\frac{g}{2\pi} \right)}{\mathbf{k}_{cor}} [m] \quad (8)$$

where T_p is the peak period ($1/f_p$). The final correction is applied for the measured tidal elevations to keep the datum consistent.

For a general water wave, the slope can be defined as $s_0 \frac{H}{\lambda}$ where H is the wave height, λ is the wavelength, and s_0 is a constant depending on the wave geometry. XBR backscatter is correlated with surface roughness (Valenzuela, 1978); therefore, when the wavefront slope is roughly perpendicular to the radar beam, the return echo is maximized. Consequently and accounting for the fact that observations only consist of H_s in terms of wave height, a regression model can be constructed as:

$$H_s = b_0 + b_1 \lambda_{99} \gamma_{1/3} \quad (9)$$

where b_0 and b_1 are the regression constants to be determined from observations, $\gamma_{1/3}$ is the mean of 1/3 of the highest raw radar signal from a patch in the middle of the domain, and λ_{99} is the 99th percentile wavelength obtained from the whole domain. The patch is chosen in the middle for $\gamma_{1/3}$ due to fact that nearshore processes are more complex (wave-wave interactions, breaking, etc.) and lower grazing angles at offshore may result in more shadowing which can alter the signal quality.

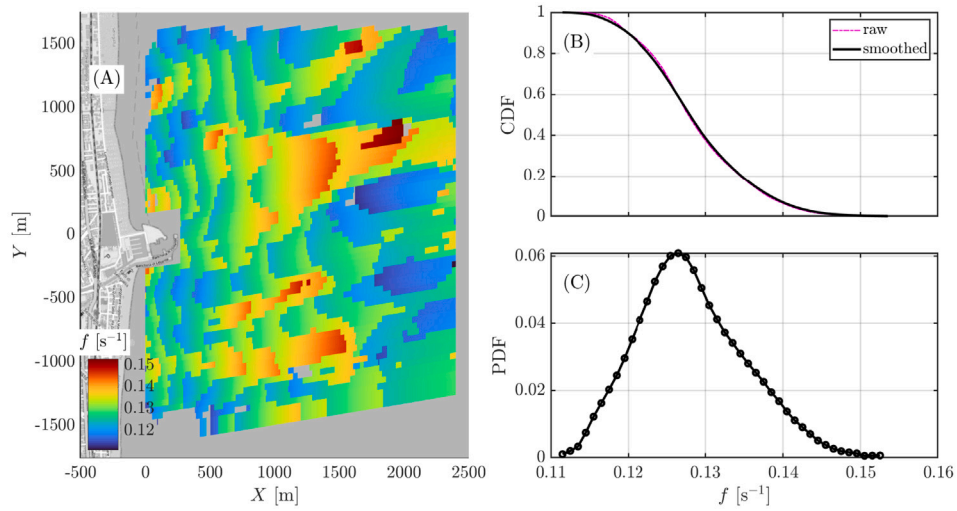


Fig. 6. A: The spatial variation of the frequencies. B: Raw and smoothed CDF obtained from histogram analyses. C: PDF obtained from the smoothed CDF.

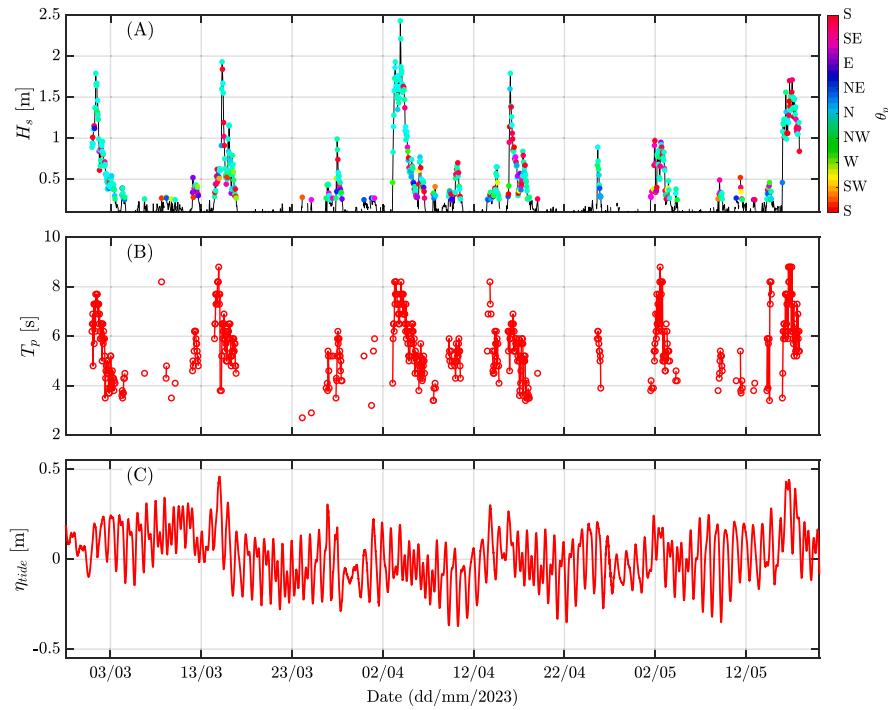


Fig. 7. Hourly observed A: significant wave height and the peak direction (colour-coded), B: peak period, and C: water level.

3.4. Alternative processing tools

The proposed methodology is developed to reconstruct the spatiotemporal evolution of wave characteristics. Therefore, alternative processing tools are utilized with the same dataset for further benchmarking, regarding the spatial limitation of in-situ measurement. The first tool is REMOCEAN (RM), which is a commercial product provided with the XBR setup (Serafino et al., 2012). RM adopts a complex procedure starting by applying 3D-FFT to get wavenumber-frequency characteristics, then a high-pass filtering is applied for power decay corrections. The surface currents are estimated and filtered from the spectrum by using the Normalized Scalar Products (NSP) method. The last filtering is done to remove electromagnetic modulation based on spectral modulation transfer functions. Finally, RM can reconstruct

the complete sea-state dynamics, including the surface currents and bathymetry.

The second tool is cBathy (CB), which is a widely used, open-source bathymetry estimation software package (Holman et al., 2013). The 3D-FFT analyses are also essential part of the CB algorithm. After transferring to the wavenumber-frequency domain, cross-spectral matrices are obtained to derive coherency between the pixels and predefined frequency pairs. Then, the spatial modes are determined by Empirical Orthogonal Functions to extract dominant wavelengths. Based on weighing the dominant frequency–wavenumber pairs, the bathymetry is estimated. Although the final product is bathymetry, CB gives an insight about the wave characteristics since the algorithm is based on the dispersion equation (Eq. (1)). The dominant wave characteristics for CB (e.g., λ_{dom}) are obtained by histogram analyses.

Table 2
Selected empirical models to predict maximum inundation, R_2 .

Proposed by	Code	Formulation
Holman (1986)	H86	$0.83 \tan \beta \sqrt{H_s \lambda_p} + 0.2 H_s$
Stockdon et al. (2006)	S06	$0.043 \sqrt{H_s \lambda_p} \Leftrightarrow \xi_p < 0.3$ $1.1 \left(\frac{\sqrt{H_s \lambda_p (0.563 \beta^2 + 0.004)}}{2} + 0.35 \beta \sqrt{H_s \lambda_p} \right) \Leftrightarrow \xi_p \geq 0.3$
Vousdoukas (2014)	V14	$0.53 \beta \sqrt{H_s \lambda_p} + 0.58 \tan \beta H_s + 0.45$
Atkinson et al. (2017)	A17	$0.92 \tan \beta \sqrt{H_s \lambda_p} + 0.16 H_s$
Power et al. (2019)	P19	$f(H_s, \lambda_p, \beta, r)$

4. Coastal inundation analyses

4.1. Empirical estimates

The most used inundation formulations were chosen to compare with FW results. The selection procedure was simply the similarity between the models and ease of applicability. All models are based on H_s , peak wavelength, λ_p , and beach slope, β except that there is an additional thresholding by Stockdon et al. (2006) based on the Iribarren number, $\xi_p = \beta / \sqrt{H_s \lambda_p}$, and incorporation of hydraulic roughness length, r , by Power et al. (2019). The latter parameter was adjusted to give similar results with other approaches (r : 10^{-3}). The selected models and corresponding equations are summarized in Table 2.

4.2. Phase-resolving model

The study site was modelled in FW to conduct inundation analyses by forcing with LMS-derived wave characteristics. In FW, waves are generated by internal wavemaker based on the spectrum constructed by given settings. Since the wavemaker accepts a single water depth, a flatbed was attached to keep the real bathymetry intact. Additionally, lateral boundaries were modified to enable periodic boundary condition to prevent shadowing due to oblique waves and reflect the complete dynamics. The spatial resolution of the model was set to 0.8 m in both directions to accurately resolve wave propagation and prevent numerical dissipation. Simulations were forced with LMS-derived wave characteristics and lasted 3600 s to capture the spatio-temporal inundation dynamics.

5. Results

5.1. Hydrodynamics

MEDA station collected data approximately 3 months, from beginning of March to mid-May in 2023. There were five relatively energetic storms where H_s was larger than 1.5 m and reached to as high as 2.5 m, dominantly propagated from North to South (Fig. 7A). Maximum T_p was observed around 8 s for all these events (Fig. 7B). The maximum tidal range was nearly 0.5 m during these events, as illustrated in Fig. 7C.

The energetic event occurred in the beginning of April was chosen to evaluate the performance of the framework in estimation of wave characteristics and bathymetry. This event was used to determine the regression coefficients to estimate the significant wave height. LMS-derived wave characteristics were compared with MEDA, RM and CB as illustrated in Fig. 8. The correlation coefficient (r_{cc}), coefficient of determination (r^2), and root mean square error (RMSE) variables were determined between observations and predictions and summarized in Appendix B. It should be noted that MEDA evaluates the wave characteristics hourly whereas XBR collects nearly 2 min of data.

The regression model for H_s gave decent results in terms of trend and values ($r^2 = 0.79$) although the peak could not be captured (Fig. 8A). RM overestimated H_s through this event despite of capturing the general trend ($r_{cc} = 0.88$, RMSE = 0.51 m, Fig. B.2). LMS, RM, and CB

gave consistent results for θ where it fluctuated around 30 degrees (Fig. 8B, B.3). However, observed θ was mostly from North direction. Small differences can be attributed to the wave refraction process but nearly 30 degrees of difference indicates another source of interference, most probably the instrumentation pole of the MEDA station.

Since sampling time was different for MEDA and XBR, MEDA results for T_p were interpolated to XBR time steps, T'_p . The leveraged period, $\bar{T}$, from CB could not give satisfactory estimations as illustrated in Fig. 8C. On the other hand, LMS and RM gave better results where RMSE was lower for RM (Fig. B.4). However, RM tended to underestimate high energetic events ($T_p > 6.5$ s) which were better captured by LMS, and both of them overestimated low energy events ($T_p < 6.5$ s). The sampling duration differs between in-situ observation (hourly) and remote sensor (2 min) which can lead to this deviation regarding the fact that low energy wind waves lean to have larger frequency bandwidth. Deep water wavelength, λ_0 , of MEDA is evaluated from T'_p based on linear wave theory and compared with the estimated wavelengths (Fig. 8D). LMS and RM showed complementary trends for λ during this event (Fig. B.5).

5.2. Morphodynamics

LMS was designed to solve the dispersion equation by using the derived wave characteristics to estimate the bathymetry. For benchmarking the methodology, LMS-derived bathymetry results were compared with ground truth data from December 2022, and results from RM and CB (Fig. 9, A–D). LMS provided a more noise-free result than RM and CB due to employment of single set of peak parameters. Kalman filtering can substantially remove the fluctuations observed in CB-derived bathymetry. However, the spatial inconsistency in wave kinematics will not improve, thus affecting the interpretation. Although the time between the field survey and XBR data did not match, it provided a relevant insight on the performance.

The MRE is characterized by three distinct regions based on the interventions such as breakwaters in the north, harbour at the centre and unprotected beach in the south. Therefore, three cross-shore transects were examined to assess the performance of LMS (Fig. 9E–G). In the south, all predictions were overestimated up to 5 m depth, yet, the seabed slope was accurately reconstructed by LMS (Fig. 9E). The eroded portion at the jetty mouth was only captured by CB with a mismatch in location, which can be attributed to the difference between surveying and data collection times. LMS slightly underestimated the water depth in the north at 2–3 m depths but demonstrated a good agreement with ground truth data along the transect. The estimation difference of LMS between north and south resulted in bifurcations for the depths shallower than 3.5 m as illustrated in Fig. 9H. The absence of Kalman filtering resulted in unrealistic undulations for CB and FFT-based approach of RM provided stair-like trends towards the offshore. However, all models were consistent in magnitudes.

In addition to visual inspections, scatter plots were created for performance assessment of LMS, CB, and RM. When the results were compared for the first dataset from 04 April 2023, LMS showed the best performance with the lowest RMSE and the highest r^2 which were 0.51 m and 0.79, respectively. Despite the high correlation of CB

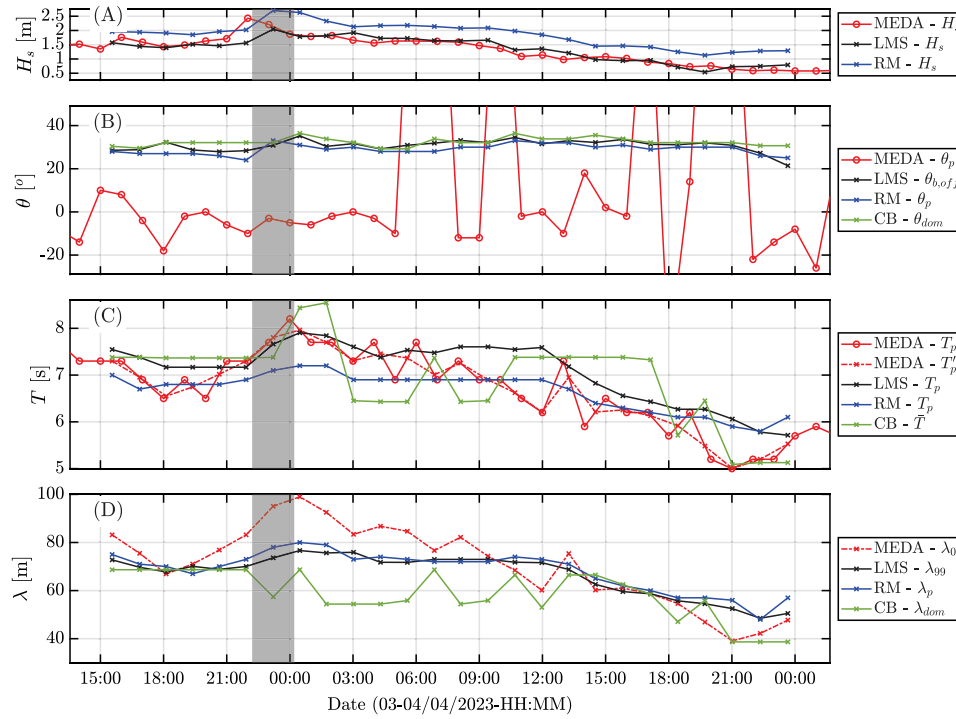


Fig. 8. Comparison of observed (MEDA) and estimated (LMS, RM, and CB) timeseries; A: significant wave height, B: wave direction, C: wave period, and D: wavelength through 3-4 April, 2023. The grey patch indicates the LMS-derived wave characteristics provided to FW.

Table 3
Average performance of processing tools for April storm.

Tool	r_{cc}	r^2	RMSE [m]	t_c
LMS	0.96	0.70	0.55	60 s
RM	0.76	0.43	0.84	90 min
CB	0.93	0.68	0.58	350 s

($r_{cc} = 0.93$), it gave the worst performance (Fig. 9E). However, when the overall performance was controlled (Table 3) through 3–4 April storm, RM was the worst performing. On the other hand, LMS and CB performed similarly in overall where LMS was moderately better, especially in the computational time, t_c .

6. Discussion

6.1. Reconstruction of sea state and bathymetry

Although the LMS methodology is based on an incoherent radar, its performance is competitive when compared with methods deriving H_s from a regression model developed for coherent radars that are capable to provide more physical aspects on sea waves by including the phase information (Carrasco et al., 2017). The reported RMSE of 0.24 m indicates that LMS can achieve a similar performance. More recently, Carrasco et al. (2024) further exploited the prominent feature of coherent radars and established a physics-based regression-free method, which were capable to yield better results. However, the demonstration was limited to offshore conditions, where the wave field has a more homogeneous behaviour than nearshore environment. Atkinson et al. (2021) showed that r^2 of 0.74 could be achieved via a signal-to-noise ratio (SNR) approach at the nearshore, where LMS provided a moderately better performance ($r^2 = 0.79$, Fig. B.2). The predictions based on radar shadowing characteristics resulted in r_{cc} and RMSE of 0.84 and 0.28 m, respectively (Zong et al., 2026), which affirms the capabilities of LMS ($r_{cc} = 0.89$, RMSE = 0.21 m).

In addition to θ_p , LMS provides the refraction evolution by which the propagation direction can differ at the harbour location from that of the offshore when the incident angles are relatively large with respect to shoreline normal. Szczyrba et al. (2023) illustrated how the spatial variability of wave processes can be prominent during storm conditions. Therefore, spatial variation of wave direction, which is usually overlooked, would be more informative than directional spectrum which is the most common directional product from existing tools (Bergsma et al., 2019; O'Dea et al., 2025). The statistical measurements on the monitoring performance of the peak period are scarce in the literature. It was proven that the peak period could be derived from the reconstructed free surface elevations by assimilating marine radar data (Greenwood et al., 2018; Simpson et al., 2020), although it requires further demonstration in terms of continuous monitoring. The peak period was estimated by Carrasco et al. (2024) with r_{cc} of 0.85 and RMSE of 1.28 s, where LMS established a satisfactory performance such that these parameters were estimated by 0.9 and 0.54 s, respectively (Fig. B.4). Although the comparisons indicate that LMS can achieve promising results, our study is limited by the small number of available datasets, owing to the scarcity of overlapping measurements.

The bulk statistics revealed that LMS can deliver fairly good performance in bathymetry estimation when compared with radar-based bathymetry inversion methods. The application of CB algorithm to marine radar images resulted in bathymetry estimates with an RMSE of 0.49 m (Honegger et al., 2019) whereas, at our study site, the CB and the LMS estimates gave RMSEs of 0.58 m and 0.55 m, respectively. Ludeno et al. (2018) showed that the NSP-based bathymetry reconstruction achieved an RMSE of 0.46 m and a regression coefficient of 0.98 for synthetic scenarios. For the real case scenario, however, the lowest RMSE increased to 1.25 m, which is higher than the RMSE reported in this study, although the regression coefficient remained high at 0.92. Rutten et al. (2016) radar-based bathymetry estimations gave larger errors for the depths smaller than 6 m, such that RMSE increased to 2.7 m. Although the RMSEs have not been evaluated separately for shallow and deep waters, there were rare instances for LMS that the errors passed the 1 m threshold (Fig. 9H). Atkinson

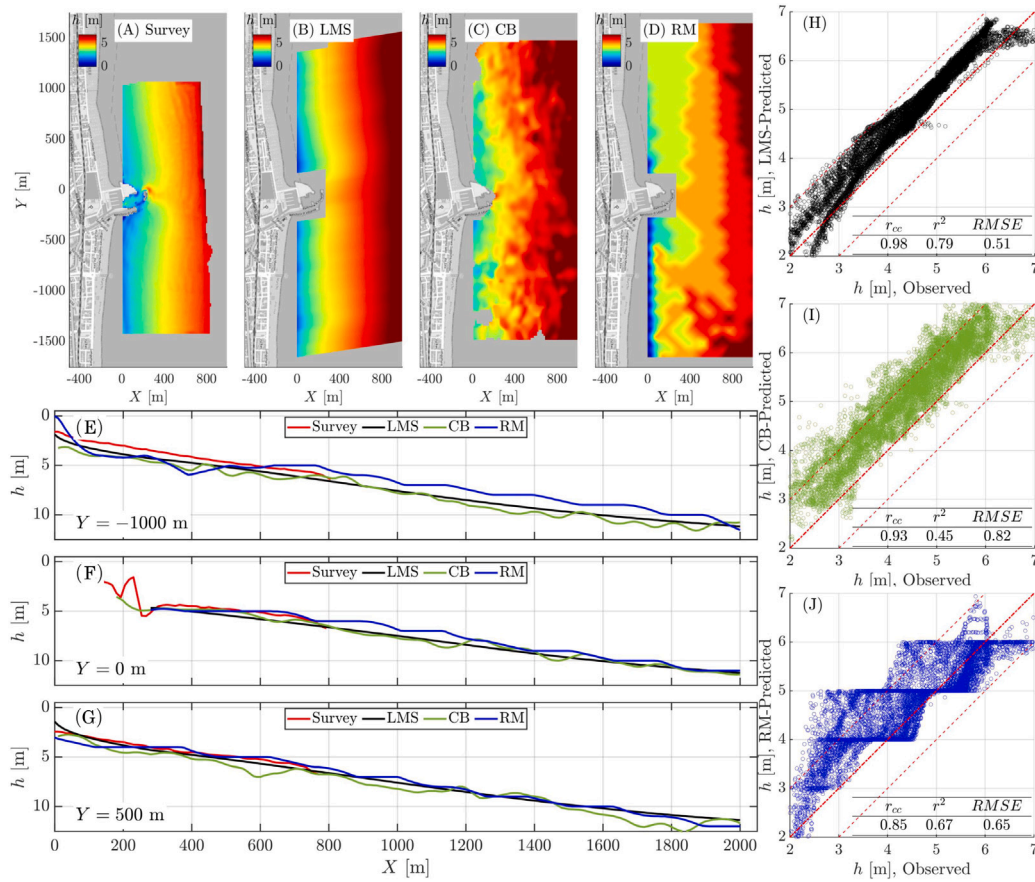


Fig. 9. Comparison of surveyed (A) and estimated (B: LMS, C: CB, and D: RM) bathymetry results on the MRE map, cross-shore bathymetry transects at $Y = -1000$ m (E), at $Y = 0$ m (F) and at $Y = 500$ m (G), and statistical comparison of estimated (H: LMS, I: CB, and J: RM) and observed bathymetry for dataset belonging to 4 April 2023, 00:30.

et al. (2021) unveiled that their radar-based methodology provided water depth estimations whose errors were 100% within the ± 1 m, whereas this was measured as 99.5% for the LMS-derived bathymetry. As mentioned before, we observed a systematic bias for all methods we tested. If the methodology is improved to eliminate this bias it can result in smaller RMSE and more confined error distribution. Both overestimation and larger errors in water depth derivation characterize video-based inversion algorithms when the wave height is greater to trigger intense breaking and nonlinear behaviour (Brodie et al., 2018) and it requires further investigations to understand these impacts of nonlinear propagation on the radar modulation.

6.2. Diagnostics and limitations

The regression coefficients of Eq. (9) were determined based on the MEDA measurements during 3-4 April storm. Therefore, another dataset from 1 March (2023) was chosen to further investigate the capabilities of LMS. Estimated wave characteristics were compared with observations and illustrated in Fig. 10.

LMS could not reproduced accurate results starting from the dataset indicated with a magenta colour. When the raw images of these event were investigated, they were strongly altered by noise, presumably, due to strong river discharge (Fig. 10E). The inspection of the particular event indicated by cyan colour revealed that the images did not contain any information related to wave propagation.

The regression model was needed further examination to better understand the its response. Therefore, the last storm during 16 May 2023 was analysed with LMS to estimate H_s and compared with MEDA and RM (Fig. 11A). In overall, LMS and RM overestimated H_s ; however,

they showed a congruent trend through this storm. The SNR approach of RM and the similarity between LMS and RM indicated that the source of error was related to XBR signals. When the images belong to data dated to 16 May 2023 were analysed by Radon transformation, clearly there was a cross-sea state that resulted in a higher radar gain and altered SNR, as demonstrated in Fig. 11B–C. Consequently, the regression model overestimated H_s values through this event similar to RM.

The magnitudes of the celerity correction applied in Eq. (7) was investigated to understand potential impacts of the approach. As illustrated in Fig. 12A, the threshold of the celerity corrections falls in $\pm 5\%$ of the mean celerity, which indicates that corrections were marginal. Moreover, T_p calculated from two fitting approaches (power and $\tanh$) were compared to investigate how sensitive the results were (Fig. 12B). It is clear that the difference between two fittings are negligible. This is an expected outcome when the celerity variations of two functions are examined in Fig. 5C as the two functions are almost identical in the cross-shore direction from 400 m to 2000 m. Consequently, they lead to similar frequencies in histogram analyses.

LMS utilizes Radon transform to track wave crest patterns in times-tack images. As waves travel towards onshore, the influence of seabed greatly increases and result in skewness that crest and trough celerities start to deviate. Such a deviation invalidates the assumption of equivalence between crest velocity and phase celerity. However, the XBR does not represent exactly the crest motion but the motion of wavefronts when the propagation is directed onshore. Therefore, the wavenumbers are calculated for the skewed waves if skewness is in action and the difference between crest and phase celerities might be compensated since spatially consistent frequency distribution could be

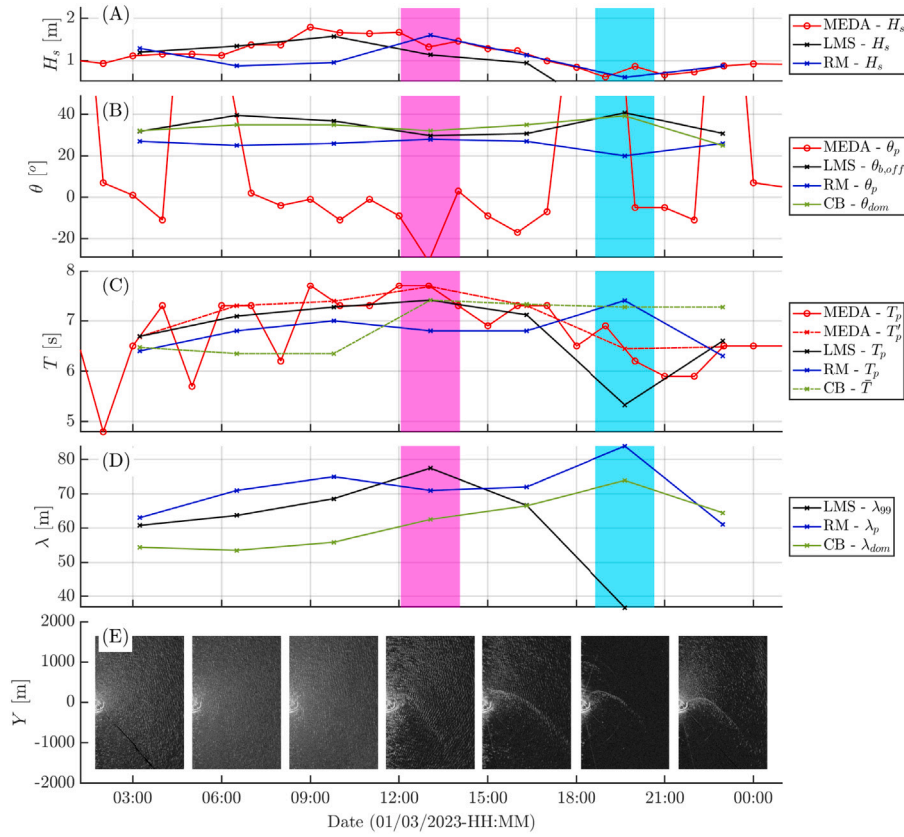


Fig. 10. Comparison of observed (MEDA) and estimated (LMS, RM, and CB) timeseries; A: significant wave height, B: wave direction, C: wave period, D: wavelength, and E: XBR images through 1 March, 2023. Magenta and cyan colours indicate the discussed events, respectively.

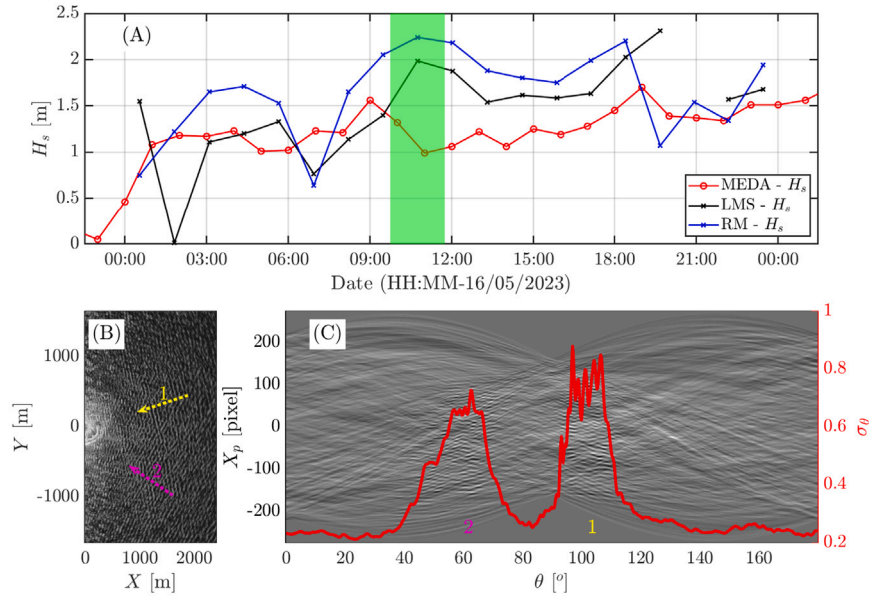


Fig. 11. A: Comparison of predicted H_s timeseries with observations during 16 May 2023. B: The XBR snapshot belonging to the event indicated by green patch. C: Corresponding Radon sinogram with double peaked variance which indicates cross-sea state.

obtained (Fig. 6A). Yet, this speculation needs a thorough investigation to understand how microwaves are modulated under different wave conditions (e.g., linear, skewed, swell). Although LMS-derived wave kinematics provide robust and reliable estimates of water depth via the linear dispersion equation, even under energetic conditions, the applicability of the linear framework may still be subject to some

limitations as nonlinear wave processes become more pronounced. Moreover, surface currents are neglected in the proposed methodology. The tide-inferred currents are relatively weak at the MRE due to the microtidal regime, however, storm conditions can trigger strong current fields. The proposed method estimates the celerity and wavenumbers explicitly, then, substitutes them into the dispersion equation to predict

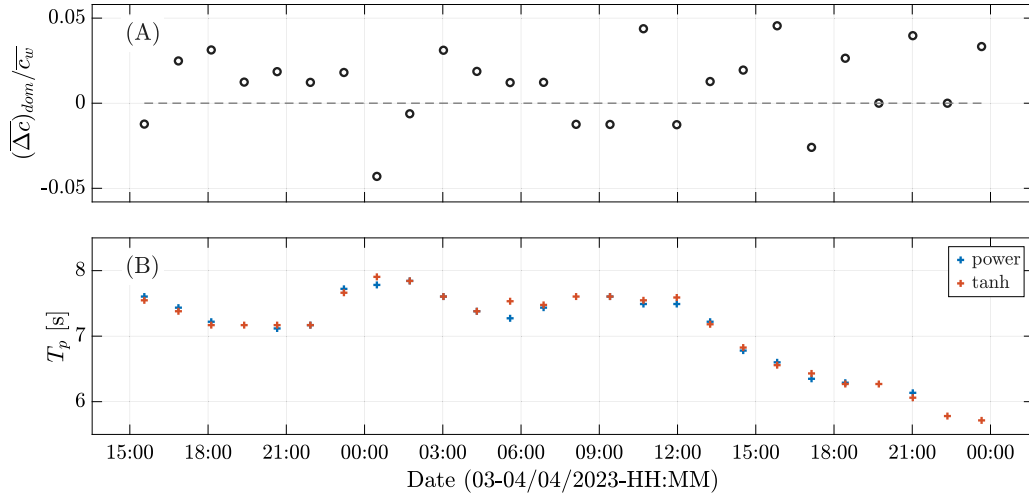


Fig. 12. A: The variation of the ratio of the celerity correction, $(\Delta c)_{dom}$, and mean celerity, $\bar{c}_w$. B: The comparison of the peak periods obtained from different celerity fittings.

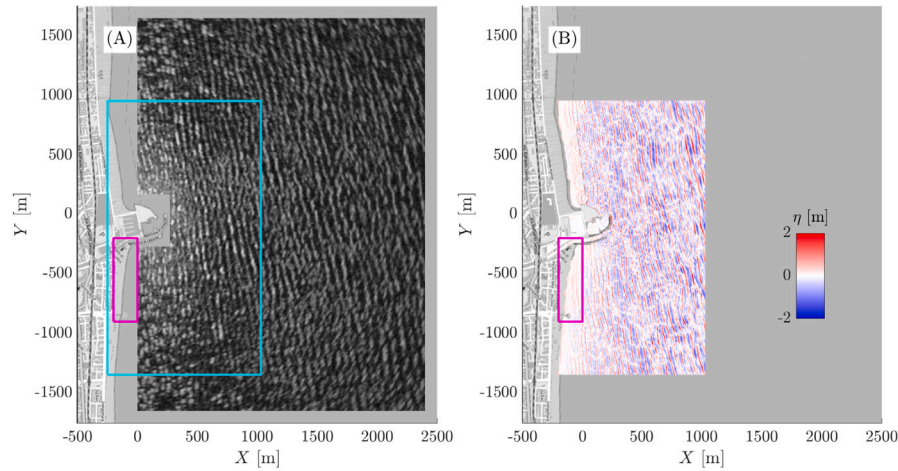


Fig. 13. A: XBR snapshot of the first dataset from 4 April 2023. B: Wave elevations obtained from FW after an hour. Cyan and magenta rectangles indicate the numerical domain and the zone where inundation dynamics were investigated, respectively.

the water depth. Therefore, the impact of currents is diffused into the wave kinematics. The absence of in-situ measurements of currents hinders a comprehensive analyses on the current impacts. Bathymetry results showed that there were no noticeable spatial variations in the errors but a constant positive bias, which can be attributed to the nonlinear wave characteristics regarding the energy conditions of the analysed datasets.

The regression model to estimate H_s depends on two parameters; λ_{99} and $\gamma_{1/3}$. The former one is derived from the reconstructed wave kinematics so that, as long as the dataset possesses a sufficient quality to complete the framework process, it can be confidently inserted into the regression model. The latter one is obtained from a relatively small patch of the entire domain. Therefore, it is more sensitive to local disturbances in the signal such that the signal histogram can be altered when the patch and local disturbance coincide.

7. Coastal inundation modelling

The most intense storm conditions derived from LMS were provided to FW to conduct inundation analyses and compare with empirical

models. Wave elevations after an hour-long FW simulation were illustrated with XBR snapshot in Fig. 13. FW-derived waves showed similar refraction patterns to XBR although they were relatively irregular than XBR signals.

The southern part (indicated in Fig. 13A) was chosen to investigate inundation dynamics. Firstly, swash events were collected each 60 s as illustrated in Fig. 14A. The alongshore variation of maximum swash lengths showed a slightly increasing trend away from the harbour, where the maximum reached to nearly 27 m. Similarly, runup events were derived from FW results (Fig. 14B). Then, the maximum runup, R_{max} events along the shoreline compared with the empirical models (Fig. 14C, Table 2). The peak location of R_{max} was slightly missed by empirical methods, except S06, which gave a fixed value. S06 underestimated and P19 overestimated the maximum runup. In addition, the results from FW showed stronger alongshore variation than all empirical models.

8. Conclusion and future perspectives

In this study, LMS framework was tested with remote sensor data from our study site, MRE. Comparisons with field observations, alternative processing tools and previous studies indicated that LMS has a

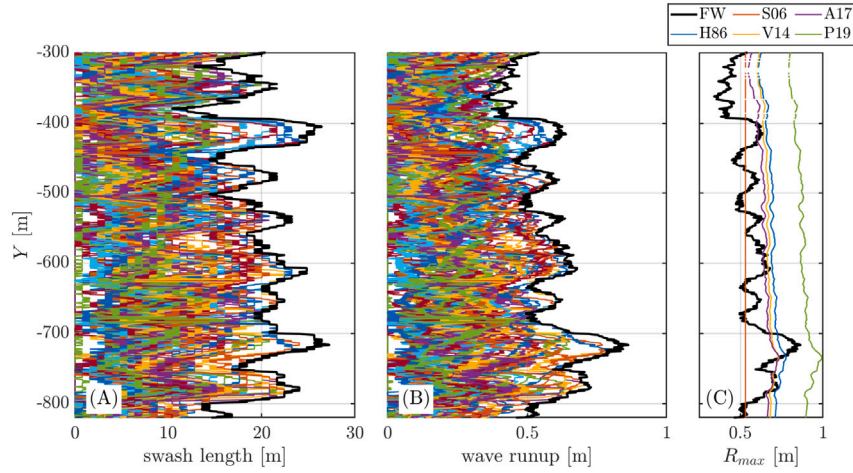


Fig. 14. Evolution of swash (A) and runup (B) events with their maxima, and C: comparison of the maximum runup with the empirical models given in Table 2.

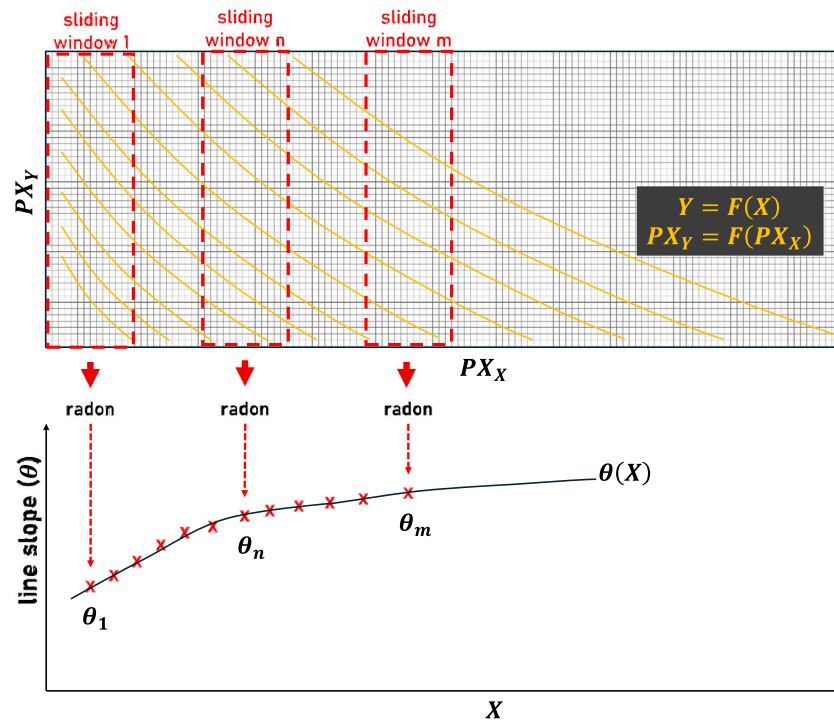


Fig. A.1. Reconstruction of the slope variation along the physical axis from an image by utilizing Radon transform.

great potential to collect information on nearshore hydro-morphodynamic processes. LMS outperformed alternative processing tools in reconstructing wave characteristics and bathymetry without compromising computational efficiency. Promising statistical measurements were obtained that the coefficients of determination of H_s and h were evaluated as 0.79 and 0.7, respectively.

The LMS-derived bathymetry resulted in a positive bias, which can be attributed to nonlinear wave process and temporal differences between data collection and in-situ measurements. LMS performance was affected by altered radar signals. However, the novel approach of LMS allowed us to further diagnose the source of the alteration. Diagnostics revealed that the cross-sea state resulted in higher radar gains due to increased roughness that in-situ devices cannot capture this physical phenomenon. In spite of these limitations, the LMS framework can provide advantageous applications owing to the significant wave height

prediction along with wave kinematics. To support this statement, the LMS-derived wave characteristics were used to conduct coastal inundation analyses with FW and the performance of empirical models were tested. The maximum inundation location and the alongshore variability could not be captured by these models. The maximum inundation was underestimated 15% in overall.

LMS is designed to collect spatio-temporal evolution of wave propagation. Therefore, more complex processes can be investigated to enhance our knowledge on nearshore dynamics, which is crucial for many coastal aspects such as resilience, continuous monitoring, and navigational safety. Ongoing efforts focused on the further investigation of these dynamics and inclusion of SGS system to resolve surf and swash zone dynamics. Eventually, it may provide more robustness and an opportunity to improve empirical models to get more reliable results and increase their accuracy.

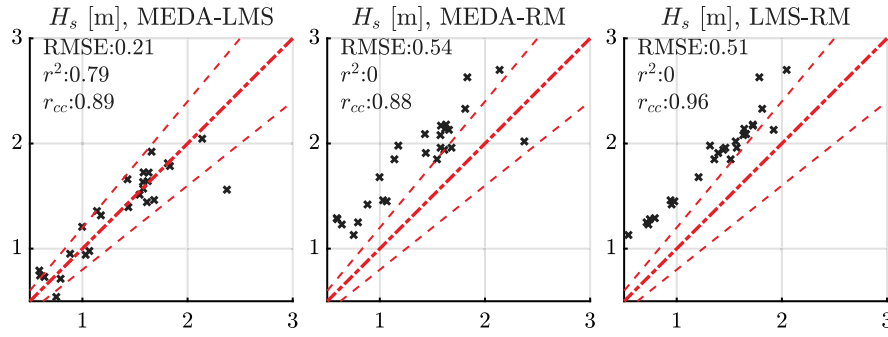


Fig. B.2. Comparison of observed and estimated H_s , and corresponding statistical measures. The horizontal (x) axis refers to the first, and the vertical (y) axis refers to the second variable. Thick and thin red lines indicate 1:1 and 20% error margins, respectively.

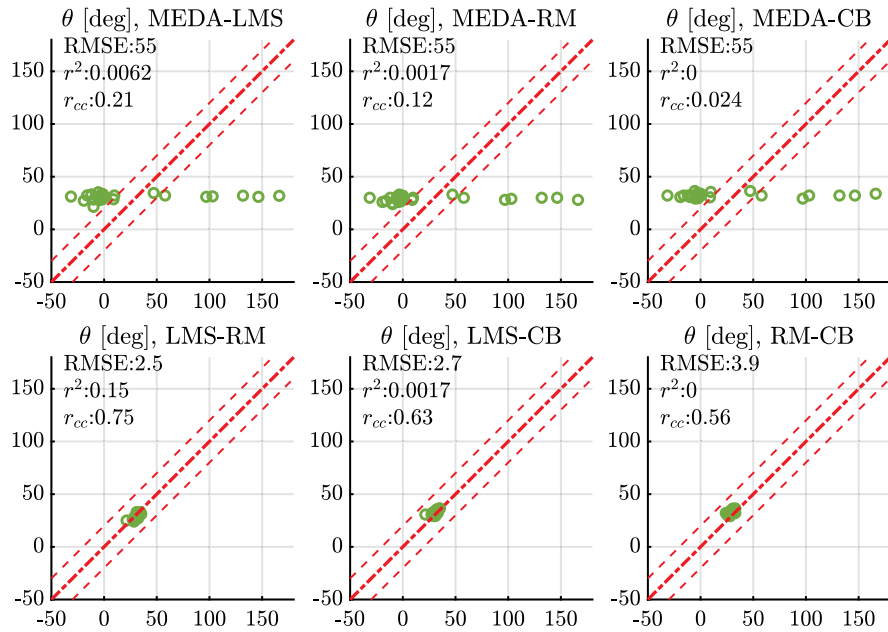


Fig. B.3. Same as Fig. B.2 but for θ .

CRedit authorship contribution statement

M. Said Parlak: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matteo Postacchini:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Maurizio Brocchini:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Radon-based pattern extraction algorithm

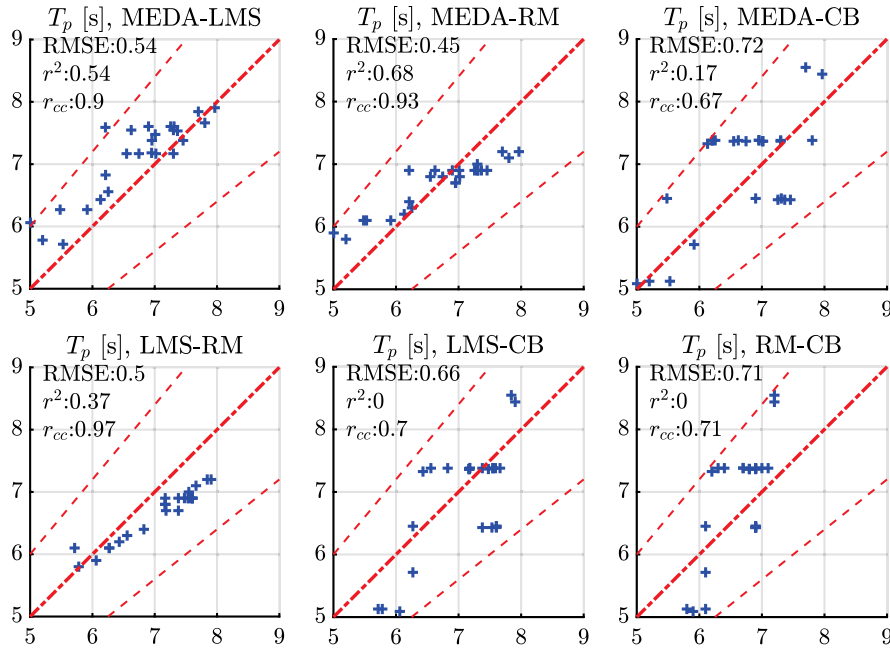
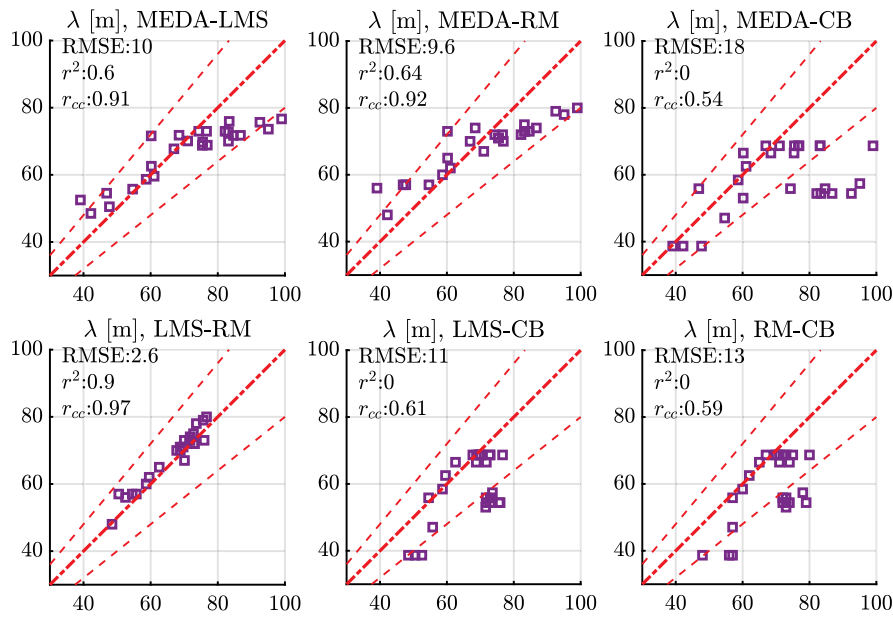
The RT is realized in pixel units, since there is no dimensional awareness. Therefore, the physical unit of a corresponding quantity (spatial or temporal) should be integrated into the constructed relation between pixel dimensions. The steps of this integration was demonstrated with following example. If we assume that we have two physical quantities X and Y with lengths of L_X and L_Y , they can be represented as pixel units as

$$PX_X = (X_{L_X} - X_0)/\Delta X, \quad PX_Y = (Y_{L_Y} - Y_0)/\Delta Y \quad (\text{A.1})$$

where the terms in parenthesis represent the last and first elements of the quantity, respectively. By applying Radon transform with sliding windows, we can determine the slope (θ) of the dominant pattern in the image, defined as $PX_Y = F(PX_X)$, along the sliding axis as demonstrated in Figure A.1. Since the relation between PX_X and X is known, we can fit a function to estimate line slope variation, $\theta(X)$, along X (see Fig. A.1).

Based on these findings, the following expression can be written;

$$\tan(\theta(X)) = \frac{\partial F(PX_X)}{\partial X} \quad (\text{A.2})$$

Fig. B.4. Same as Fig. B.2 but for T_p .Fig. B.5. Same as Fig. B.2 but for λ .

By rearranging Eq. (A.1) and discretely integrating Eq. (A.2), one can find corresponding physical points in

$$Y = \left(\sum_{i=1}^{L_X} \tan(\theta_i) \Delta X \right) \Delta Y + y_0 \quad (\text{A.3})$$

where y_0 is a constant.

Appendix B. Statistical analyses

The statistical measurements were conducted not only between observations and estimations, but also between the LMS and alternative

tools. The mathematical equations of corresponding statistical measures are defined as: for Pearson's correlation coefficient

$$r_{cc} = \frac{\sum_{i=1}^n (z_i - \bar{z})(\hat{z}_i - \bar{\hat{z}})}{\sqrt{\sum_{i=1}^n (z_i - \bar{z})^2} \sqrt{\sum_{i=1}^n (\hat{z}_i - \bar{\hat{z}})^2}}, \quad (\text{B.1})$$

for coefficient of determination

$$r^2 = 1 - \frac{\sum_{i=1}^n (z_i - \hat{z}_i)^2}{\sum_{i=1}^n (z_i - \bar{z})^2}, \quad (\text{B.2})$$

and for root mean square error

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i - \hat{z}_i)^2} \quad (\text{B.3})$$

where z_i is the predicted, $\hat{z}_i$ is the observed, $\bar{z}$ is the mean predicted, $\bar{\hat{z}}$ is the mean observed variable and n is the number of observations. The comparisons are demonstrated as scatter plots along with statistical variables in the subsequent figures.

Data availability

The measurements of MEDA station can be accessed on the following website: <https://www.irbim.cnr.it/sitoss-dettagli/stazione-meteo-marina-senigallia/>. The measurements of tide gauge can be accessed on the following website: https://tsunami.isprambiente.it/TAD_Server/Device/178. The bathymetry data from ISMAR can be found at the following address: http://cigno.ve.ismar.cnr.it/layers/geonode:single_beam_bathymetry_adriaticsea#more.

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