

Document Version

Final published version

Licence

CC BY

Citation (APA)

Overes, P. H. P., Borsje, B. W., Luijendijk, A. P., White, R. D., Roetert, T. J., & Hulscher, S. J. M. H. (2026). Estimating sand wave migration from local hydrodynamics and sediment mobility. *Geomorphology*, 514, Article 110517. <https://doi.org/10.1016/j.geomorph.2026.110517>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

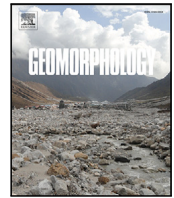
In case the licence states "Dutch Copyright Act (Article 25fa)", this publication was made available Green Open Access via the TU Delft Institutional Repository pursuant to Dutch Copyright Act (Article 25fa, the Taverne amendment). This provision does not affect copyright ownership.
Unless copyright is transferred by contract or statute, it remains with the copyright holder.

Sharing and reuse

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.



Estimating sand wave migration from local hydrodynamics and sediment mobility

Pauline H.P. Overes^{a,b}, Bas W. Borsje^a, Arjen P. Luijendijk^{b,c}, Ruben D. White^b,
Tom J. Roetert^b, Suzanne J.M.H. Hulscher^a

^a University of Twente, Marine and Fluvial Systems, Enschede, The Netherlands

^b Deltares, Delft, The Netherlands

^c Delft University of Technology, Faculty of Civil Engineering and Geosciences, Delft, The Netherlands

ARTICLE INFO

Keywords:

Marine dunes
Tidal sand wave migration
In-situ measurements
Delft3D flexible mesh
Hydrodynamics
Dutch continental shelf
Offshore engineering

ABSTRACT

Sand waves are large migrating seabed features that are widespread on sandy continental shelves. Their migration causes seabed level changes that can affect offshore infrastructure, motivating the need for decadal-scale predictions of migration rates. Common prediction approaches rely on extrapolation of historical observations and are therefore difficult to apply in data-scarce regions or under changing environmental conditions. To satisfy the need for quick process-based estimations of sand wave migration, we explore relations between hydrodynamic forcing, sediment mobility, and sand wave migration. We calculated and verified sand wave migration rates across the Dutch Continental Shelf, including ~14,500 km of sand wave crests. Using hydrodynamic conditions from the Dutch Continental Shelf Model and sediment grain size and water depth measurements, we derived migration rate estimators based on driving processes. Results show that an estimator based on tidal current asymmetry provides a reasonable first-order estimate of site-specific migration rates with strong linear correlation. Including non-tidal forcing improves estimates, especially for slowly migrating sand waves. By incorporating sediment mobility through excess velocity and shear stress estimators, more consistent non-linear relations are found that better reflect sediment transport physics and reduce regional differences in predictor performance. The strongest relation is obtained using squared excess velocity, while excess shear stress proves more robust when sediment grain size is uncertain. Sensitivity analyses further show that both sediment size and bed roughness influence estimator performance. These process-based estimators enable first-order migration rate predictions in data-scarce areas and provide quantitative estimates of how environmental changes affect sand wave dynamics.

1. Introduction

Due to ambitious green energy goals and population growth, the use of the offshore area is increasing at a rapid pace. Our shallow seas offer opportunities for a wide range of functions, such as energy and food production and transportation of goods. This has not gone unnoticed. The European Union is, for instance, aiming to expand offshore wind capacity to 300 GW by 2050, a twelvefold increase from the current 25 GW (European Commission, 2022). The North Sea, with its favourable wind conditions and extensive shallow waters, will play a central role in this expansion. To support the development of this offshore infrastructure, it is vital to gain insight into the dynamics of the seabed. The seabed is not flat, but contains a range of dynamic bedforms of different shapes and sizes. Of these especially sand waves deserve our attention due to their significant dimensions and persistent dynamics.

Offshore sand waves are formed by the interaction between tidal currents and sandy seabeds (Hulscher, 1996). These interactions form rhythmic bed patterns with crests perpendicular to the tidal currents and wavelengths in the order of hundreds of metres (Damen et al., 2018). Their heights may reach up to 25% of the water depth (Francken et al., 2004) (generally in the order of 1–10 m) and they can migrate with rates up to tens of metres per year (Van der Meijden et al., 2023; Van Landeghem et al., 2012). This migration can therefore cause significant bed level variations over time (e.g. Fig. 3), which in turn can cause exposure of cables and pipelines and bury objects in the seabed (Németh et al., 2003).

Sand wave migration, the movement of sand waves in a direction more or less perpendicular to their crest, can be caused by a range of factors. The primary driver is often the long-term asymmetry in

* Corresponding author at: University of Twente, Marine and Fluvial Systems, Enschede, The Netherlands.
E-mail address: p.h.p.overes@utwente.nl (P.H.P. Overes).

<https://doi.org/10.1016/j.geomorph.2026.110517>

Received 26 February 2026; Received in revised form 26 August 2026; Accepted 31 August 2026

Available online 8 September 2026

0169-555X/© 2026 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

tidal forcing, caused by superimposed tidal components (Besio et al., 2004) or residual currents (Németh et al., 2002). These residual currents themselves vary temporally due to meteorological conditions, amplifying or dampening migration rates (Overes et al., 2024). The underlying bathymetry also plays a role: sand banks can drive sand waves to migrate towards the bank crest from both sides (Leenders et al., 2021). Where suspended sediment transport and free surface waves are dominant, these processes can further enhance migration (Van Gerwen et al., 2018; Campmans, 2018), as does the scarcity of sediment (Nnafie et al., 2023). Finally, extreme events such as tropical storms can significantly alter sand wave dynamics, even mobilizing otherwise stable bedforms (Bao et al., 2020).

Three broad approaches exist to predict future sand wave migration and associated bed level change: data-driven extrapolation of observed trends, numerical process-based modelling, and (process-based) empirical relations linking sand wave and/or environmental characteristics to observed migration. Below we discuss the first two and their limitations, before introducing the empirical approach pursued in this study.

Long-term bed level predictions are, in practice, commonly obtained using data-driven analyses. In this type of analysis sand wave migration rates are determined based on historic bathymetry data and used to extrapolate the current bed level to a future moment in time (e.g. Deltares (2023), Dorst (2009)). Due to the lack of other validated approaches, this is currently the industry standard for multi-decadal bed level predictions. This approach works best for steady migration and struggles with short-term (intra- or inter-annual) variability, e.g. due to seasonal effects. To ensure robust estimates of the migration rate preferably at least three bathymetric measurements are used, which cover a temporal period of multiple years to allow for identifying trends, depending on the migration rate. However, this amount of data is not always available. Moreover, these types of analyses are generally not based on driving processes, but linearly extrapolate trends towards the future. This makes them unsuitable to deal with changing conditions due to for example climate change or human interventions.

Alternatively numerical modelling can be used to simulate sand wave dynamics and directly provide future bed levels (e.g. Krabbendam et al. (2021) and Overes et al. (2025)). These high-resolution numerical models are able to capture the effect of variable forcing conditions and future changes. However, they are relatively time-consuming in terms of preparation and computation and are not yet able to accurately capture multi-decadal sand wave evolution due to the accumulation of small morphological errors as a result of necessary numerical schematizations. On the other hand, numerical models can provide insights into the hydrodynamic forcing conditions leading to sand wave migration on a larger scale, without recreating all the details of the bathymetry. These less detailed simulations take significantly less time to run and may for large areas of the world be readily available. By creating empirical relations which capture the hydrodynamic forcing leading to sand wave migration we can greatly enhance our abilities to make first-order migration rate estimations.

A third approach is to derive (process-based) empirical relations between sand wave and/or environmental characteristics and observed sand wave migration. Attempts have been made to create such empirical relations describing sand wave migration, for example by Knaapen (2005) based on sand wave characteristics and by Li et al. (2011) combining characteristics with hydrodynamic drivers. However, these predictors rely on the asymmetry index of sand waves to estimate both migration direction and migration rate, assuming that the sand waves migrate towards their steepest slope. Although this is often the case, more recent observations by Van Landeghem et al. (2012) show that sand waves may also migrate towards their gentle slope, thereby questioning the suitability of shape-based predictors. Moreover, in both cases the relations are based on a limited number of datapoints, thereby risking overfitting. On a larger scale Van der Meijden et al. (2023) determined the migration rates of sand waves over the full

Dutch Continental Shelf, based on 25 m resolution data. They found a positive correlation between this migration rate and both the tidal peak velocity difference between flood and ebb currents, as a measure of tidal asymmetry, and the shields parameter, as a measure of sediment mobility. However, this analysis was rather limited and further analysis of these relations in future work was encouraged. If such process-based empirical relations are found they could combine the strengths of both alternatives. Unlike data-driven extrapolation, they are grounded in driving processes, allowing them to remain valid under changing conditions and in data-scarce areas. Moreover, they avoid the computational cost and accumulation of morphological errors over multi-decadal timescales, often related to process-based numerical sand wave models, while still capturing the relevant hydrodynamic forcing.

Even though the availability of data has skyrocketed over the past decade, we still lack robust, process-based estimators describing sand wave migration rates based on hydrodynamic drivers. The aim of this study is to derive estimators based on hydrodynamic forcing and sediment mobility that describe observed sand wave migration rates. These estimators improve our understanding of migration drivers and enable first-order predictions in data-scarce areas. They can also provide insights into future changes in migration rates under changing environmental conditions, such as climate change, and reveal the relative contributions of different drivers. Based on our understanding of the physical system, we define estimators that represent asymmetry in hydrodynamics and sediment mobility. These estimators can be derived solely from large-scale models or in-situ measurements. To ensure robustness, we leverage extensive datasets of derived sand wave migration rates from White et al. (2026) and sediment property measurements across the Dutch Continental Shelf. Sand wave migration rates are verified using Van der Meijden et al. (2023) and hydrodynamics are extracted from the Dutch Continental Shelf Model (Deltares, 2022).

2. Methods

In this section the data sources for bathymetric, sediment property and hydrodynamic data are described. Moreover, it outlines the methods used for determining both sand wave migration rates and hydrodynamic estimators. The data used by Van der Meijden et al. (2023) have a limited spatial resolution of 25 m, and their migration rate determination method (crest-point matching) is sensitive to measurement errors and shape changes. Therefore, we redetermine the migration rates in this study using 5 m resolution data and a 2D cross-correlation approach. This higher-resolution methodology increases the accuracy and robustness of the migration rate determination and allows for the inclusion of shorter time intervals between measurements, which were excluded by Van der Meijden et al. (2023) due to insufficient detectable migration at 25 m resolution. The data and results from Van der Meijden et al. (2023) are used here for verification purposes.

2.1. Field data

To determine sand wave migration rates, bathymetric data is necessary. For this study around 4000 bathymetric datasets are applied, which include both Multi Beam Echo Sounder (MBES) and Single Beam Echo Sounder (SBES) measurements. Most of the data is provided by the Dutch Hydrographic Office (NLHO), which can be extracted via Deltares (2017). This data is supplemented with measurements done in assigned windfarm zones to support offshore wind developments by the Netherlands Enterprise Agency, available via Netherlands Enterprise Agency (2025). Finally, a limited amount of data is provided in cable corridors by Tennet and in sand mining areas by Rijkswaterstaat. All MBES data has a resolution of at least 5×5 m. The quality of the SBES data is examined and attention is given to: (1) whether the survey lines align with the sand wave migration direction (approximately perpendicular to the crest), (2) whether the along line resolution is high

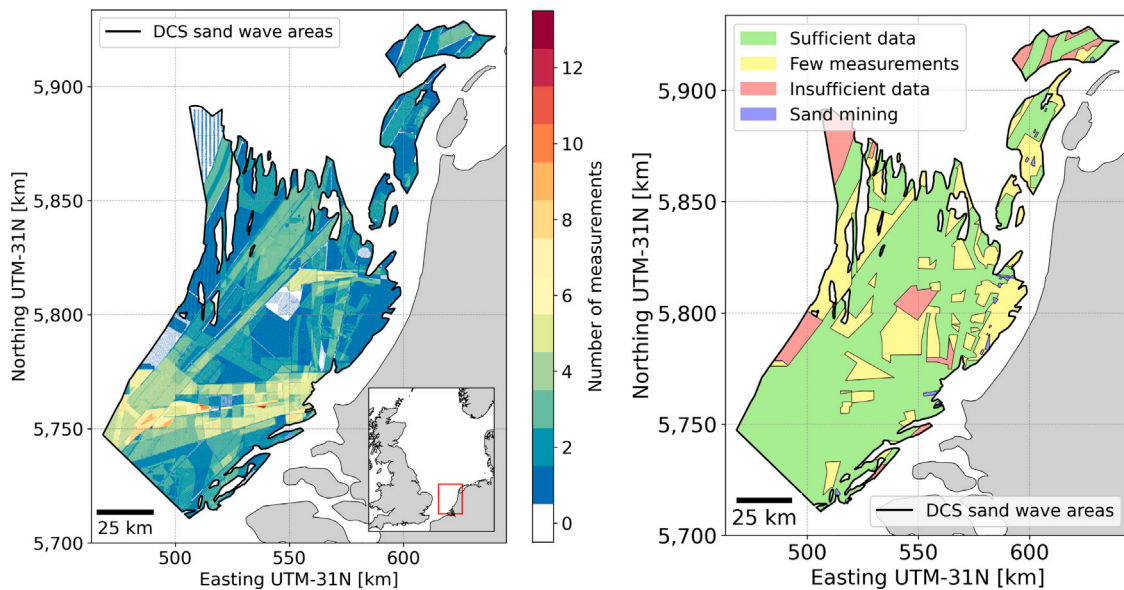


Fig. 1. Spatial overview of the amount of bathymetry datasets available from public datasources, including SBES data, which show up as stripes if widely spaced (left) and the interpretation of this coverage (right) showing if amount of measurements after quality assessment is: sufficient (> 2), few (2) or insufficient (< 2). Note at least two datasets are needed to extract migration rates. Inset plot in left Figure shows location in the North Sea.

enough (min. 5 m) and (3) whether the spacing between lines is limited enough (sufficient coverage, max ~ 100 m). A first check of the line direction and resolution is done manually, after which the coverage is checked automatically.

To determine migration rates at least two surveys are necessary, but preferably more surveys are used to increase the robustness of the estimate and account for temporal variability in the migration rates. Most of the Dutch Continental Shelf (DCS) is included at least twice in the available data, see Fig. 1. For these areas, the quality of the data is assessed, giving special attention to SBES data and the presence of human interventions in the measurement period. More recent MBES data typically has a horizontal measurement uncertainty of a few decimetres, up to half a metre (e.g. 0.4 m in Fugro (2016), see International Hydrographic Organization (2020)), while older (SBES) data may have significantly higher uncertainty. Especially in areas with low migration rates this may interfere with the determination of the sand wave migration rate. This evaluation yielded 8140 km² (67.5%) of the total sand wave areas, with sufficient data coverage where at least three datasets are available of good quality and coverage, see ‘sufficient data’ areas in Fig. 1. In other areas only 2 surveys were left after quality assessment (‘few measurements’), increasing the uncertainty of the determined migration rates, or even less than 2 measurements were available, making migration rate determination impossible (‘insufficient data’).

In addition to the bathymetric data also data on sediment characteristics is applied in this study, to allow for the determination of sediment mobility. This data is extracted from DINOLOKET (DINOLOKET, 2007) and interpolated from point data by Maljers and Gunnink (2007) to create spatial coverage of the full DCS. In this interpolation also pre-existing knowledge on grain size distribution over sand waves was incorporated (Damen et al., 2018). To prevent this from interfering with the results the grain size data was averaged over a 1 km length scale. From this data the determined median sediment diameter (d_{50}) for the top layer is used. On the DCS relatively good coverage of sediment grain size data is found, which is exceptional due to the costliness of retrieval and processing of sediment samples. Nevertheless even with good coverage and careful interpolation, still artifacts like single outlying samples are found, see Fig. 2. Comparison with interpolated top layer sediment sizes (d_{50}) from Ploeg et al. (2025), which covers an area close to shore, shows a Mean Absolute Error of around 40 μm between

the datasets. Since these studies are largely based on the same data, this indicates some dependency on interpolation choices. In addition EMODNET bathymetry data (EMODnet, 2024) is used to determine the depth of the large scale bathymetry, excluding sand waves, through smoothing and resampling to a 0.005 degree grid. This data is based on NLHO measurements (Deltares, 2017). A spatial overview of this data is shown in Fig. 2.

2.2. Migration rate derivation

To determine the sand wave migration rates, the relatively computationally intensive 2D cross correlation method is used (White et al., 2026), which yields highly robust results. This method finds the spatial shift with the highest correlation between two measurements. This results in lower sensitivities relative to methods only looking at characteristic points (such as crests, troughs or ‘zero-crossings’), which are also influenced by shape adaptations. Moreover by applying a 2D method the migration direction is simultaneously determined and may vary spatially.

The migration rates are determined through the following steps are taken, which are applied to 5×5 km square areas, excluding a buffer area. This approach reduces computation time and memory usage. First the sand wave bathymetry is separated from the underlying bathymetry using a lowpass Fourier filter with a wavelength of 1700 m. This ensures that all sand waves, with wavelengths of hundreds of metres (Damen et al., 2018), are preserved, while larger bed features such as sandbanks, with wavelengths of 5–10 km, and slopes of the continental shelf are removed. Through trial-and-error it was found that this filter size resulted in the best filtering of larger bed features, while preserving sand waves, throughout the different areas. It should be noted that with an area as large as the DCS, using one filter size is always a compromise (different sizes may work better in different areas). Then the smaller bedforms, such as megaripples with wavelengths of tens of metres, are filtered from this resulting sand wave bathymetry using a highpass filter with a wavelength of 100 m. The purpose of this filtering step is to isolate sand wave dynamics from smaller-scale bedforms. Although megaripples can contribute substantially to local seabed variability (with heights in the order of decimetres), they generally migrate on much shorter timescales than sand waves and are commonly treated as a source of bed level uncertainty rather than as individual features for

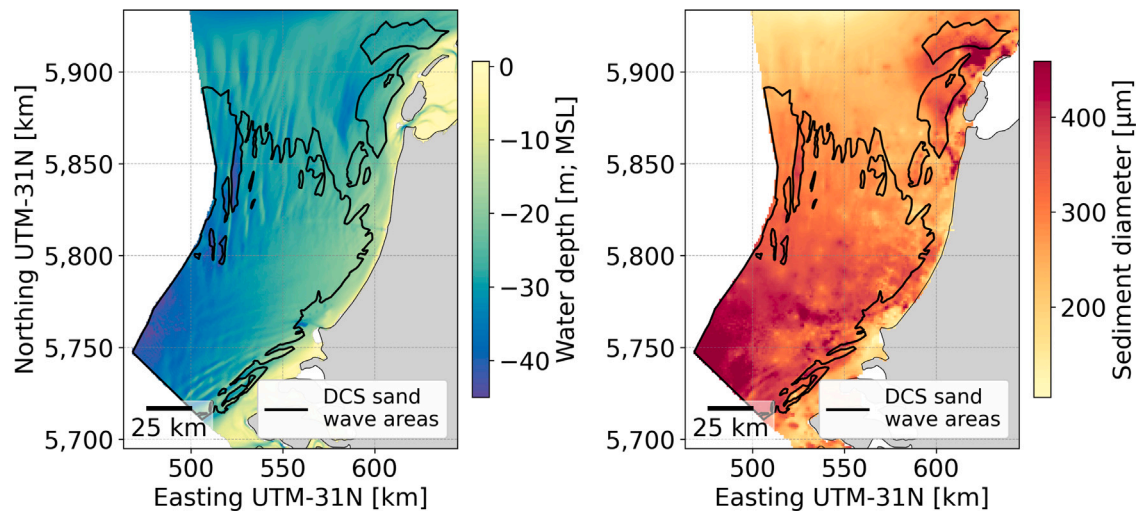


Fig. 2. Spatial overview of the depth with respect to Mean Sea Level (MSL) of the large scale bathymetry from EMODNET (EMODnet, 2024) (left) and the median sediment grain size d_{50} for DINOLoket data (DINOLoket, 2007) (right).

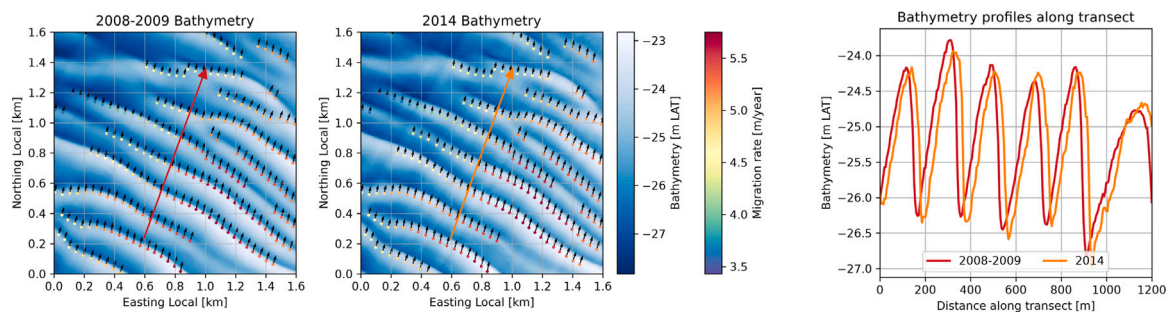


Fig. 3. Example of sand wave migration between two measurements from 2008–2009 (left) and 2014 (middle), including bed level along a transect (right) indicated with an arrow in bathymetry plots. Dots indicate derived migration rate, plotted at crest points but derived using 2D cross correlation. Origin of the plot (0,0 coordinate) is located at $x = 603$, $y = 5892$ km (UTM-31N), within the Texel-Vlieland area.

long-term migration prediction. The filtering step is therefore intended to isolate the sand-wave signal and obtain robust estimates of sand wave migration rates.

The sand wave crest locations are then determined from the sand wave bathymetries using 1D transects in the approximate migration direction. This direction is determined from the most common direction among the 5% steepest slopes. Transects are spaced 50 m apart to sufficiently capture spatial variability. Centred around these crest points, a square window of 500 m $\times$ 500 m is used for the cross correlation. This window size balances the need for localized data (not too large) with reducing noise (not too small). In areas with short wavelengths this covers the full sand wave, while preventing the inclusion of multiple sand waves. For longer sand waves this covers most of the steep slope, but only part of the gentle slope. For each combination of measurements the window is shifted from its position at the predefined crest point in the earliest measurement to find the best match in the later measurement and determine migration distance and direction, see Fig. 3. This distance is translated to a migration rate using the survey dates. The migration rates are averaged between the different survey combinations at the crest point to calculate the mean migration rate. Finally the migration rates are spatially averaged using the points within a 200 m radius to reduce noise. This procedure is described in more detail in White et al. (2026) and is similar to methods used in many commercial applications (e.g. Deltares (2023, 2016)). With a 50 m spacing over the sand wave crests this yields 466,479 data points in the areas with sufficient data.

2.3. Verification of observed migration rates

The calculated mean migration rate is verified using the migration rates from Van der Meijden et al. (2023). They determined the migration rates using 25 $\times$ 25 m resolution data (relative to 5 m in our dataset) and by applying the Pairs of Source and Target Points method (Dong, 2015). This method quantifies migration distance and direction by measuring the (shortest) distance between vectorized morphological components. In the study by Van der Meijden et al. (2023) both crest and trough lines are used to determine these migration characteristics. Since the accuracy of this method is limited by the resolution of the data (25 $\times$ 25 m) they decided to only include measurement timeseries longer than five years. Although this method is sensitive to shape adaptations because it uses only characteristic points (crests and troughs) of the sand waves, it may still outperform the 2D cross-correlation approach under specific conditions. Especially when the sand waves have few unique features (such as bends and bifurcations), the 2D cross correlation may struggle to find the exact location of the migrated sand wave. In that case this method may wrongfully assume that the sand wave has migrated slightly sideways leading to an increased migration rate. Therefore, verifying our data with Van der Meijden et al. (2023) ensures robustness.

For each crest point in our analysis, we identify the closest data point containing a crest migration rate from Van der Meijden et al. (2023), within a radius of 100 m. Data points from our analysis are retained only when their migration rate differs by less than 25% OR less than 1 m/year from the corresponding migration rate reported by Van der Meijden et al. (2023). If no data is found within this radius, the data

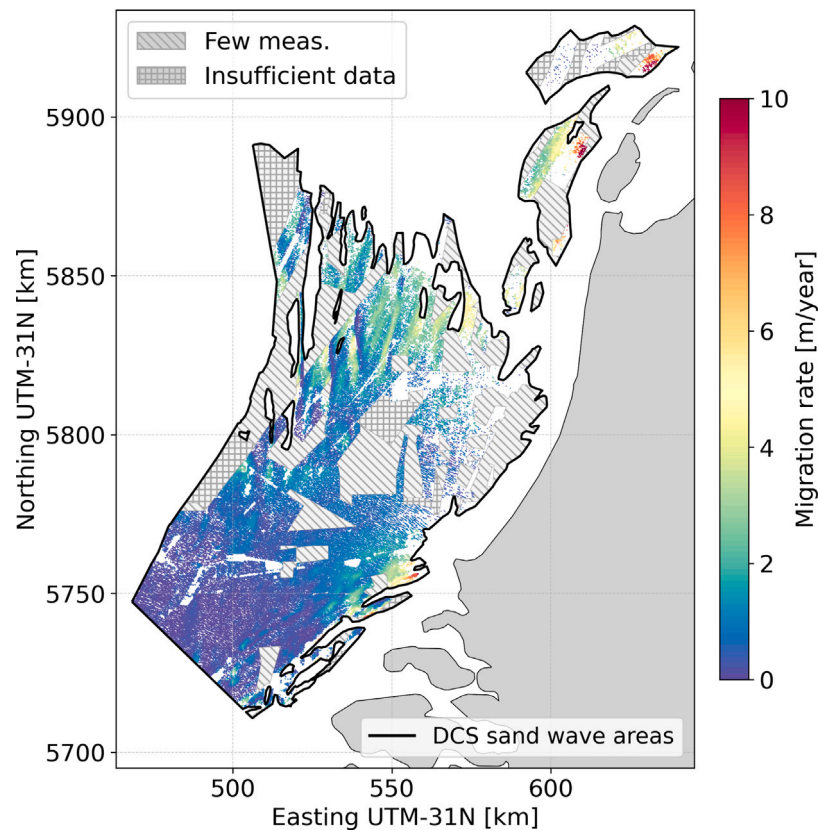


Fig. 4. Sand wave migration rate determined using 2D cross-correlation and filtered based on verification with migration rates from Van der Meijden et al. (2023). Black boundary shows sand wave areas, grey hatched areas within bounds did not contain sufficient data to robustly estimate migration rates, see Fig. 1.

point is excluded. This yields 336,201 data points, meaning that 72% of the data passed the verification. Although some data may have been wrongfully filtered out due to inaccuracies in Van der Meijden et al. (2023), the remaining data shows robust results irrespective of method and resolution and therefore the verification and filtering allows for increased trust in the migration rate data.

Additional filtering is carried out based on the variance in the derived migration rate between the different survey combinations. The DCS is known for relatively stable sand wave migration (Menninga, 2012). Therefore, high variation between the determined migration rates from different survey combinations are predominantly related to survey inaccuracies and uncertainties in migration rate derivation. Since the migration rate derived by Van der Meijden et al. (2023) is based on a subset of the same data, errors due to survey inaccuracies are not filtered through verification with their data. Therefore, additional filtering is applied to limit the effect of survey inaccuracies on the included migration rates. Only if the migration rate variation (= max migration rate - min migration rate) is less than the mean migration rate OR less than 2 m/year are the data points retained for further study. After this additional filtering step 291,758 data points remain, meaning that another 10% of the data is excluded. With a spacing of 50 m this translates to close to 14,500 km of sand wave crests. The remaining data is shown in Fig. 4. The data points which did not pass the verification are shown in the Supplementary Materials.

2.4. Hydrodynamics and bed shear stress estimators

To characterize the hydrodynamic conditions the 2D (depth-averaged) Dutch Continental Shelf Model (DCSM) is applied (Deltares, 2022). Besides tidal forcing this large scale Delft3D FM model includes meteorological forcing through spatially varying wind fields and atmospheric pressure, thereby resolving storm surge and other non-tidal

water level and current variations. Atmospheric pressure effects are incorporated through inverse barometer corrections and wind stress is calculated using a relative wind formulation. As a depth-averaged barotropic model, DCSM does not explicitly resolve wave-induced processes, density-driven circulation, or other baroclinic effects. The model is validated using field data from the southern North Sea, using both waterlevels, see Deltares (2022), and (depth-averaged) current velocities, see Deltares (2020). From this validation it was concluded that the 2D model is especially suitable for deriving depth-averaged currents offshore. For deriving currents closer to shore or at a certain depth in the water column it is recommended to instead use the 3D version of the model. Since our sand waves are located sufficiently offshore, with the ones closest to shore at approximately the same distance as the ‘offshore’ buoys in the Hollandse Kust Zuid and Hollandse Kust Noord windfarm areas used for model validation (Deltares, 2020), it is deemed acceptable to use the 2D DCSM model. In the southern North Sea the grid size is 0.5 nautical mile (approximately 0.9 km). For each cell within the sand wave domain an observation point is added and the hydrodynamic conditions are calculated. The statistics described below are calculated for each grid cell and then interpolated to the migration rate data point locations using cubic interpolation. Two model runs are used to determine the hydrodynamic conditions, one using only tidal forcing and one including all forcing conditions. The tide-only simulation covers 8 spring neap cycles. The run including non-tidal forcing is run for 25 spring-neap cycles (370 days, from July 1st 2018 to July 6th 2019) to include all seasons. Due to the wide range of time periods on which the migration rates are based, it was not possible to exactly match the bathymetry measurement period for all sand wave data points. However, with a full year of data temporal variations in non-tidal currents are sufficiently captured and use of a different time period did not significantly affect the results.

Different measures are used to quantify the hydrodynamic drivers of sand wave migration. First, the mean peak velocity difference is

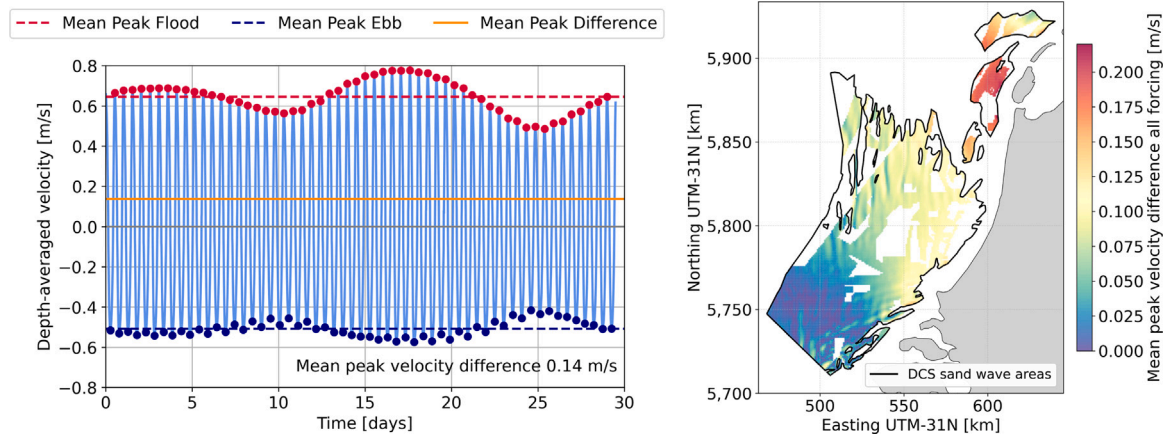


Fig. 5. Example of mean peak velocity difference calculation (left) and calculated mean peak velocity difference from full forcing run over 25 spring-neap cycles (right) using a 30 day time frame for visual purposes. Real calculations use a time frame of 8 (tidal) or 25 (full forcing) spring-neap cycles.

Table 1

Structure of a selection of bed load transport formulations. The exponent column gives the power applied to the excess-of-critical driving term (typically non-dimensional). The additional scaling column lists any multiplicative factor involving the driving variable that is applied outside this excess-of-critical term.

Bed load formula	Driving variable	Excess-critical exponent	Additional scaling	Reference
Soulsby/Van Rijn	Current velocity (u)	2.4	$*u$	Soulsby (1997)
Meyer-Peter-Müller	Bed shear stress (τ_b)	1.5		Meyer-Peter and Müller (1948)
Van Rijn 1984	Bed shear stress (τ_b)	1.5–2.1		Van Rijn (1984)
Van Rijn 1993	Bed shear stress (τ_b)	1.5	$*u_b^{0.5}$	Van Rijn (1993)
Van Rijn 2007	Bed shear stress (τ_b)	1	$*u_b^{0.5}$	Van Rijn (2007)

calculated to quantify the long-term asymmetry between flood- and ebb-directed peak currents. This difference is commonly used as a measure of tidal asymmetry and showed a positive correlation with migration rate in Van der Meijden et al. (2023). To determine this measure the peaks in both flood and ebb direction are identified in the depth-averaged velocity signal including all forcing conditions. Then the time-average peak velocity for both the flood and ebb peaks are calculated separately (based on 8 and 25 spring-neap cycles for the tidal and full forcing run respectively). The mean peak velocity difference ($u_{\text{mean peak dif}}$ [m/s]) is defined as the absolute difference between the long-term average flood peak velocity ($u_{\text{peak,flood}}$) and ebb peak velocity ($u_{\text{peak,ebb}}$). This procedure is described in Eq. (1) and shown in Fig. 5.

$$u_{\text{mean peak dif}} = \|u_{\text{peak,flood}}\| - \|u_{\text{peak,ebb}}\| \quad (1)$$

To account for sediment mobility, we calculate the excess velocity and excess bed shear stress. These variables represent the amount by which the hydrodynamic forcing exceeds the critical threshold for sediment transport, which depends on water depth and sediment size. Bed load transport rates are often assumed to be proportional to these variables (to a specific power). Examples of this are the use of excess shear stress in the Meyer-Peter and Müller and several of the Van Rijn formulations (Meyer-Peter and Müller, 1948; Van Rijn, 1984, 1993, 2007), and the use of excess velocity in the Soulsby/Van Rijn formula (Soulsby, 1997; Van Rijn, 1993), see Table 1. First the critical bed shear stress is calculated based on the Shields parameter. For the critical Shields parameter (θ_{cr}) calculation an approximation of the Shields curve from Van Rijn (2007) is used. For the considered sediment sizes (200–600 μm), the calculation of the dimensionless particle size (D_*) is fixed and this comes down to:

$$\theta_{cr} = 0.013 (D_*)^{0.29}, \quad D_* = d_{50} [(s-1)g/\nu^2]^{1/3} \quad (2)$$

where d_{50} is the median sediment diameter [m]. s represents the relative density of the sediment with respect to water, assumed to be 2.65 [–]. g is the gravitational acceleration (9.81 m/s^2) and ν is the

kinematic viscosity of water, which is taken as $1 \times 10^{-6} \text{ m}^2/\text{s}$. Using the critical Shields parameter the critical bed shear stress ($\tau_{b,cr}$ [N/m^2]) can be calculated as follows:

$$\tau_{b,cr} = (\rho_s - \rho_w) g d_{50} \theta_{cr} \quad (3)$$

where ρ_w is the density water (taken as 1025 kg/m^3) and ρ_s is the density of soil ($2.65\rho_w = 2716 \text{ kg/m}^3$). The critical depth averaged velocity (u_{cr} [m/s]) can be calculated from this critical shear stress using:

$$u_{cr} = \sqrt{\frac{\tau_{cr} C^2}{\rho_w g}} \quad (4)$$

where C is the Chézy roughness [$\text{m}^{1/2}/\text{s}$], which is calculated following Colebrook and White (1937):

$$C = 18 \log_{10} \left(\frac{12H}{k_s} \right) \quad (5)$$

In this formula H represents the total water depth [m]. k_s is the bed roughness height [m], which accounts for grain and form roughness. This bed roughness height is set at 0.03 m based on the presence of ripples, with an average length (λ_r) of 0.17 m (as observed by Damveld et al. (2018)) and an average ripple height (Δ_r) of 0.017 m, assuming a steepness (H/λ_r) for current ripples of 0.1 (Van Rijn, 1993). The ripple roughness is calculated using the formula proposed by Van Rijn (1993) ($k_{s,r} = 20\gamma_r \Delta_r * (\Delta_r/\lambda_r)$, where γ_r is a ripple presence factor, set at 0.7 for ripples superimposed on sand waves) and combined with the grain roughness ($k_{s,grain} = 3d_{90}$, $d_{90} = 1.5d_{50}$). In reality the roughness will vary based on ripple dimensions and shape and sediment characteristics (even between sand wave crest and trough, see Damveld et al. (2018)). However, there is insufficient data available to base such a varying bed roughness on.

The critical velocity and shear stress are then used to calculate the excess velocity and excess shear stress, by subtracting these from the time varying signals (while bounded at zero). The time-varying, depth-averaged velocity is extracted at 10 min intervals and interpolated to

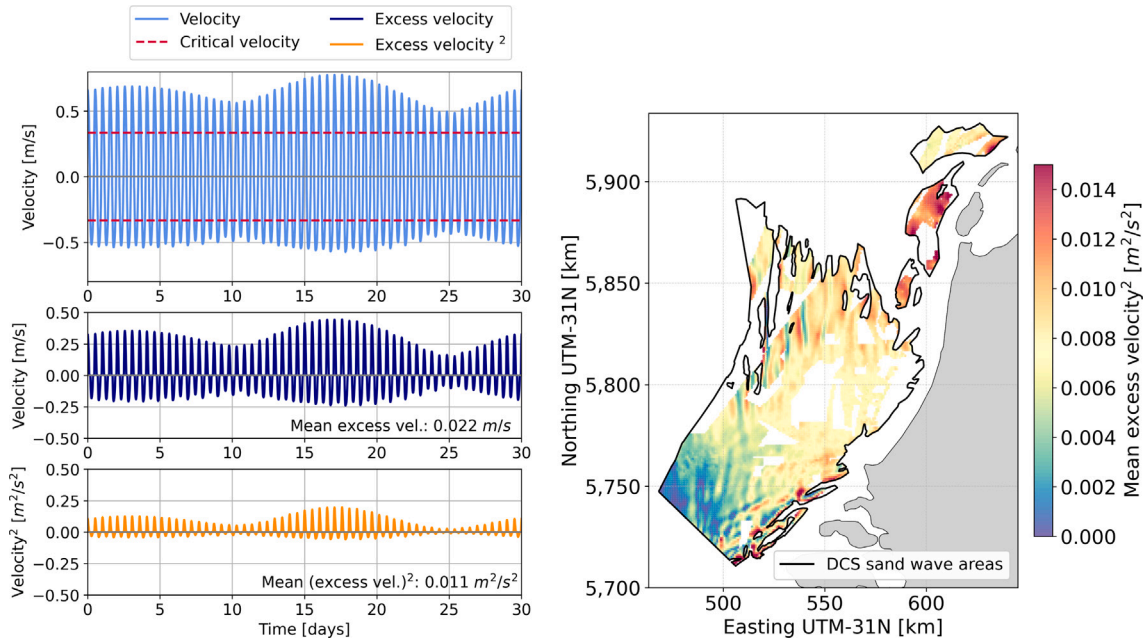


Fig. 6. Example of mean excess velocity calculation (left), for exponents $n = 1$ (middle window) and $n = 2$ (lower window) and calculated mean excess velocity with $n = 2$ (squared) from full forcing run (right) using a 30 day time frame for visual purposes. Real calculations use a time frame of 8 (tidal) or 25 (full forcing) spring-neap cycles.

the sand wave crest locations. From this depth-averaged velocity (u), the time-varying bed shear stress is calculated as follows:

$$\tau_b = \rho_w g \frac{u^2}{C^2} \quad (6)$$

From the velocity and bed shear stress signals the critical values are subtracted to calculate the excess velocity and excess bed shear stress:

$$u_{\text{excess}} = \max(|u| - u_{cr}, 0) \quad (7)$$

$$\tau_{b,\text{excess}} = \max(|\tau_b| - \tau_{b,cr}, 0) \quad (8)$$

Since sediment transport is often assumed to be non-linearly related to the excess velocity or excess bed shear stress, we will apply an exponent (n) before time-averaging the signal. This is done as follows:

$$u_{\text{mean excess}, n} = \overline{u_{\text{excess}}^n} \quad (9)$$

$$\tau_{b,\text{mean excess}, n} = \overline{\tau_{b,\text{excess}}^n} \quad (10)$$

The rationale behind these estimators is that sand wave migration is driven by asymmetry in sediment transport rather than by asymmetry in current velocity itself. Classical bed-load transport formulations are nonlinear once the critical threshold for sediment motion is exceeded, see Table 1. By introducing a critical threshold and applying a power (n) before temporal averaging, the proposed estimators mimic the structure of these transport relations and provide a proxy for long-term transport asymmetry. In this way the relatively larger contributions of extreme conditions are maintained and not averaged out, for example, against excess velocities with half the magnitude, which are present for twice as long. The values of n considered in this study are $n = 1, 2$ and 3 for the mean excess velocity, and $n = 0.5, 1$ and 1.5 for the mean excess bed shear stress. These include a case without additional velocity scaling ($n = 1$ for excess velocity and $n = 0.5$ for excess bed shear stress) and two exponent values representative of commonly used bed load transport formulations ($n = 2$ and 3 for excess velocity; $n = 1$ and 1.5 for excess bed shear stress; see Table 1). The excess velocity and bed shear signal are averaged over the full signal (containing for a large part zero values due to below critical conditions) to take into account all conditions capable of transporting sediment. The length of this signal

is 8 spring-neap cycles (≈ 4 months) for the tidal run and 25 spring-neap (≈ 1 year) for the full forcing run, ensuring a representative signal. This process is shown in Fig. 6 for the velocity case with exponents of $n = 1$ and $n = 2$.

Although the excess velocity and excess bed shear stress estimators are mathematically related through the proportionality $\tau_b \propto u^2$, they are not equivalent. In the excess velocity approach, the critical threshold is applied before the nonlinear transformation, whereas in the excess bed shear stress approach the threshold is applied after transforming velocity into bed shear stress. This leads to different sensitivities to the threshold of motion. The bed shear estimators respond stronger when just surpassing the critical conditions, but are in the higher mobility ranges less sensitive to the exact threshold for motion.

2.5. Error and association metrics for estimator evaluation

For each of the hydrodynamic and sediment mobility estimators considered in this study, a relation of the form $y = ax^{\text{exp}} + b$ is fitted between the estimator (x) and the observed migration rate (y). The values for a , b and the exponent are obtained by minimizing the Median Absolute Error (MdAE, defined below) between the observed and predicted migration rates, in which the value of the exponent is selected from a predefined set of positive values. When local fits are made for a subset of the data, the value of the exponent is prescribed based on the global fit to ensure comparability. To evaluate the variability between the fits for subsets of the data the coefficient of variation (CV) is used. This coefficient is calculated based on the mean (μ) and standard deviation (σ) of the fit coefficients using:

$$CV = \frac{\sigma}{\mu}$$

To evaluate the performance of the migration rate estimators, we use three complementary metrics: the Mean Absolute Error (MAE), the Median Absolute Error (MdAE), and the correlation ratio (η). The MAE quantifies the average absolute deviation between the observed values (y_i) and the predicted values ($\hat{y}_i$), which are in this study estimated using a fitted relation. Its units match those of the variable (in our case m/year). The MAE is calculated as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

here n is the total number of data points and i the specific data point considered. Since the MAE is a mean, it is sensitive to the small subset of data points with large absolute errors. To complement the MAE with a measure that is more representative of the typical, bulk performance of an estimator, we additionally report the Median Absolute Error (MdAE):

$$\text{MdAE} = \text{median } i = 1, \dots, n (|y_i - \hat{y}_i|).$$

Because the median is a robust statistic, the MdAE is far less influenced by a limited number of poorly predicted data points than the MAE. Comparing MAE and MdAE therefore indicates the extent to which an estimator's overall error is driven by a small tail of large deviations rather than by a systematically poor fit throughout the dataset: a large gap between MAE and MdAE points to the former, while similar values indicate a consistent error across the full range of the data.

To assess the strength of association we use the correlation ratio (η). This measure of association captures any relationship between two variables, whether linear, non-linear, or non-monotonic, without assuming a specific functional form (Draper and Smith, 1998). To calculate η , the predictor variable (x) is first divided into k equal-width bins (in this study taken as 30). The correlation ratio is then defined as the fraction of the total variance in y that is explained by the variation in the bin-wise mean values of y :

$$\eta^2 = \frac{SS_{\text{between}}}{SS_{\text{total}}} = \frac{\sum_{j=1}^k n_j (\bar{y}_j - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad \eta = \sqrt{\eta^2}.$$

where k is the number of bins, n_j and $\bar{y}_j$ are respectively the number of data points and the mean of y within bin j , and $\bar{y}$ is the mean of y over the full dataset. Bins containing fewer than 5 points are excluded from the calculation, to avoid bin means being disproportionately affected by a small number of points. The correlation ratio is then obtained by taking the square root. Since η is bound between 0 and 1, values close to 1 indicate that knowing the value of the predictor variable strongly determines the value of the migration rate, while values close to 0 indicate no association. Because η does not assume linearity, it can be directly compared between the linear (e.g. mean peak velocity difference) and non-linear (e.g. mean excess velocity, mean excess bed shear stress) estimators used in this study, without being biased in favour of either functional form. For a strictly linear relationship, η approaches the absolute value of the Pearson linear correlation coefficient; for non-linear relationships, η will generally exceed it, reflecting the additional association that Pearson's coefficient fails to capture.

3. Results

To investigate the ability of the hydrodynamic and sediment transport estimators to describe and predict sand wave migration rates, we correlate these statistics with the observed migration rates. The analysis includes all 291,758 verified migration-rate data points across the DCS. First, we explore how well sand wave migration can be explained using hydrodynamic conditions alone, through the mean peak velocity difference. Then we will add the mobility of sediment, to make a better informed estimation of asymmetry in the sediment transport, using the mean excess velocity and bed shear stress. Finally, we will see how dependent these estimations are on spatial sediment data, since acquiring this type of data is often quite costly.

3.1. Relations between hydrodynamics and migration rates

First, we will explore how well the sand wave migration can be explained by looking purely into hydrodynamic conditions. To describe the long-term tidal asymmetry, which is believed to be one of the main drivers for sand wave dynamics, the mean peak velocity difference is calculated as described in Eq. (1) and shown in Fig. 5. This is done for both the run with only tidal forcing and the full forcing run. When

only tidal forcing is included (Fig. 7A), there is a strong correlation between the sand wave migration rate and the mean peak velocity difference, with a correlation ratio (η) of 0.75. Moreover, a linear fit can describe the data with a Mean Absolute Error (MAE) of 0.494 m/year and a Median Absolute Error (MdAE) of 0.265 m/year. Although this is generally good enough for a first estimate, it is still high considering the low migration rate of the considered sand waves (1.1 m/year on average). The large difference between the MAE and the MdAE indicates that a small subset with large errors significantly affect the MAE, which is also clearly visible in Fig. 7A as spread in the data points.

When all forcing conditions are included, the correlation becomes slightly stronger, with η increasing to 0.78. The MAE and MdAE of the linear fit decrease to 0.477 and 0.217 m/year, respectively (Fig. 7B). The inclusion of meteorologically driven non-tidal forcing (wind and atmospheric pressure effects) is particularly beneficial for the correlation in the low migration rate ranges (< 1 m/year). For this subset, the correlation ratio increases from 0.56 to 0.67 (not shown). In the south-western parts of the DCS the added non-tidal currents counterbalance the tidal asymmetry and therefore explain the local immobility of sand waves. In other parts of the DCS, the non-tidal currents enhance the present tidal asymmetry and thereby amplify sand wave migration. Both effects can clearly be distinguished in Fig. 7, where the data is better concentrated around the linear fit when non-tidal currents are included, especially for low migration rates.

Interestingly, part of the data shows a much higher mean peak velocity difference, forming a separate patch from the rest of the data. These sand waves are located in the isolated fields near the Dutch Wadden islands of Texel and Vlieland. To study these spatial differences in more detail we have divided the data into nine areas, based on the areas applied in Van der Meijden et al. (2023), see Fig. 8. These areas group the data into approximately equally sized groups (before filtering), loosely based on environmental characteristics (water depth, presence of sandbanks) and sand wave characteristics and dynamics. The migration rates in the Texel-Vlieland area are also higher than those in most other areas, reasonably matching the linear fit. However, based on the non-linear relation between current velocity and sediment transport even higher migration rates would be expected. This mismatch can be explained by the lower mobility of sediment in this area. The peak ebb currents are close to the critical velocity, while the peak flood currents slightly surpass them. In these lower mobility ranges a similar change in velocity will cause a lower change in sediment transport compared to the case where peak currents amply surpass critical values. Peak tidal current asymmetry does not account for the ability of the currents to transport sediment. As a result, it can overestimate or underestimate the asymmetry in sediment transport. Therefore a measure including the threshold of motion will be better able to explain and describe the physical system in the areas with peak currents close to this threshold.

The relationship between mean peak velocity difference and migration rate varies substantially among the different areas of the DCS (Fig. 8). The highest-density regions in the plots generally align with the overall linear fit. However, when individual areas are considered separately, substantially different regression relationships are obtained. In the IJmuiden-Texel area (lilac), for instance, the local fit is significantly steeper, while based on other areas like Noordhinder South (purple) and Zeeland Banks (yellow), the local fit is more gentle. In the Texel-Vlieland and IJmuiden-Maasvlakte areas the fit based on MdAE optimization even results in negative relations between mean peak velocity difference and migration rate. This variability between the fitted relations is reflected in the coefficient of variation for the fit parameters a and b ($y = ax + b$), which are 1.44 and 3.27 respectively. This variation between the local fitted relations complicates finding an overall estimator sand wave migration rate based on the mean peak velocity difference when data-availability is limited.

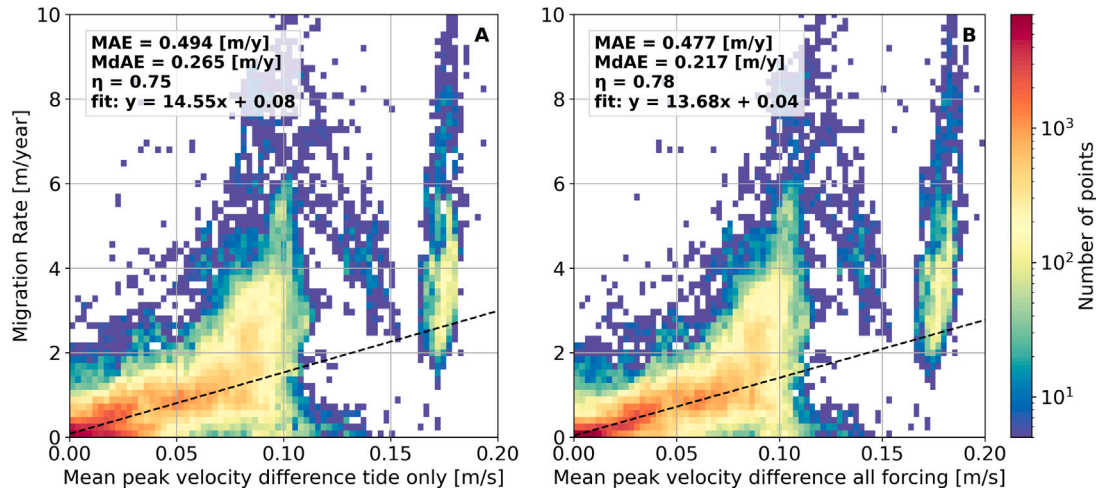


Fig. 7. Density plot of sand wave migration rate against the mean peak velocity difference for the case with tide-only forcing (A) and all forcing conditions (B). Included statistics are the correlation ratio (η) and the Mean/Median Absolute Errors (MAE + MdAE) to the (linear) fit shown with the dotted line.

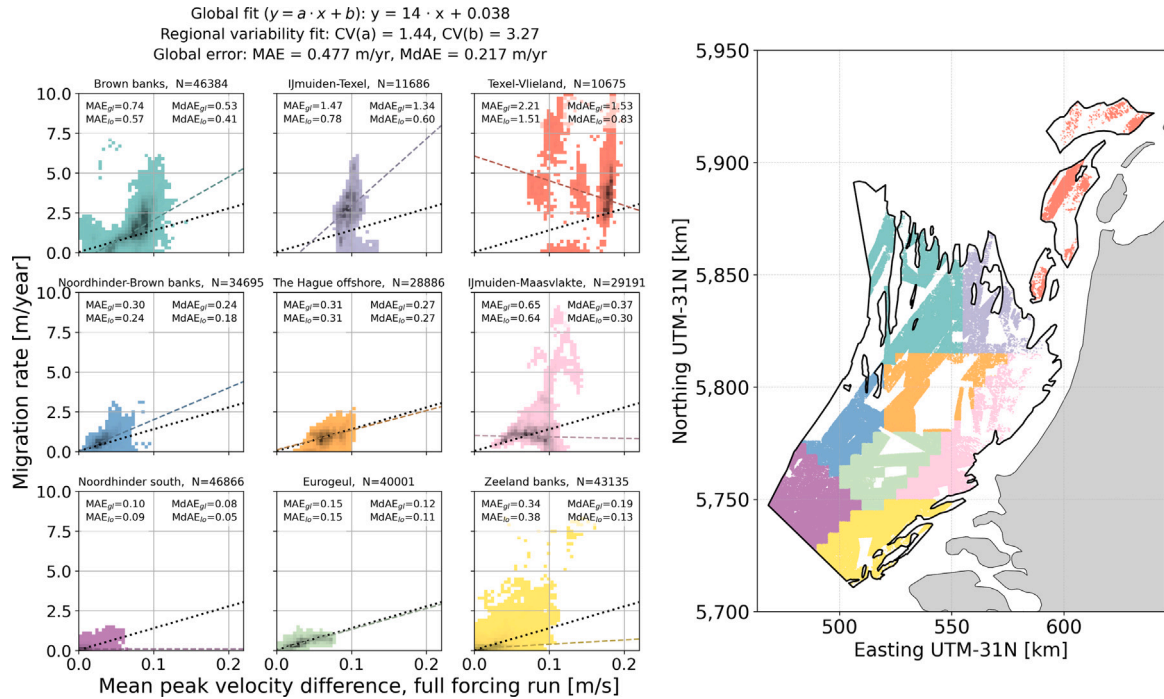


Fig. 8. Mean peak velocity difference from the run including meteorological forcing compared to sand wave migration rate per area including the global linear fit (black dotted line) and a local linear fit for that area (coloured dotted line). Darker areas show higher point density. Plot titles indicate number of points in the area (N). Within each plot the MAE and MdAE with the global (gl) and local (lo) linear fit.

3.2. Relations between migration rates and sediment mobility

To investigate whether the sand wave migration estimators can be improved by including sediment mobility, we will consider the mean excess velocity and mean excess bed shear stress estimators (see Eq. (9) and (10)). These take into account the threshold for sediment transport based on the local sediment grain size. Through the use of an exponent before averaging, the variables mimic the structure of sediment transport relations, thereby offering a measure for asymmetry in sediment transport for exponents of 2 and 3 in case of excess velocity and 1 and 1.5 in case of excess bed shear stress. Fig. 9 shows the fit for the mean excess velocity with exponents (n) of 1, 2 and 3 in the upper row. Especially with $n = 1$ or 2, the mean excess velocity shows a clear non-linear fit with the migration rate, with a MAE of 0.59 and 0.49 m/year and a MdAE of 0.29 and 0.23 m/year for the

respective exponents. Especially with $n = 2$, a clear non-linear relation appears with the migration rate, which is reflected in the higher value for the correlation ratio (η) of 0.724. Moreover, the relation for $n = 2$ is no longer divided into two separate areas and the Texel-Vlieland sand wave data attaches to the rest, showing one overall fit. With this exponent the error statistics are in the same range as those for the mean peak velocity difference, although the correlation ratio is still slightly lower. When the exponent further increases to a third power ($n = 3$), the sand waves with the higher migration rates (Texel-Vlieland, IJmuiden Texel and Brown banks areas) do not align with the non-linear fit anymore. In these areas with high migration rates the asymmetry in the mean excess velocity decreases when a higher power is applied. The observed optimum around $n = 2$ aligns well with sediment transport theory because it falls within the range of nonlinear exponents commonly applied in sediment transport formulations, see

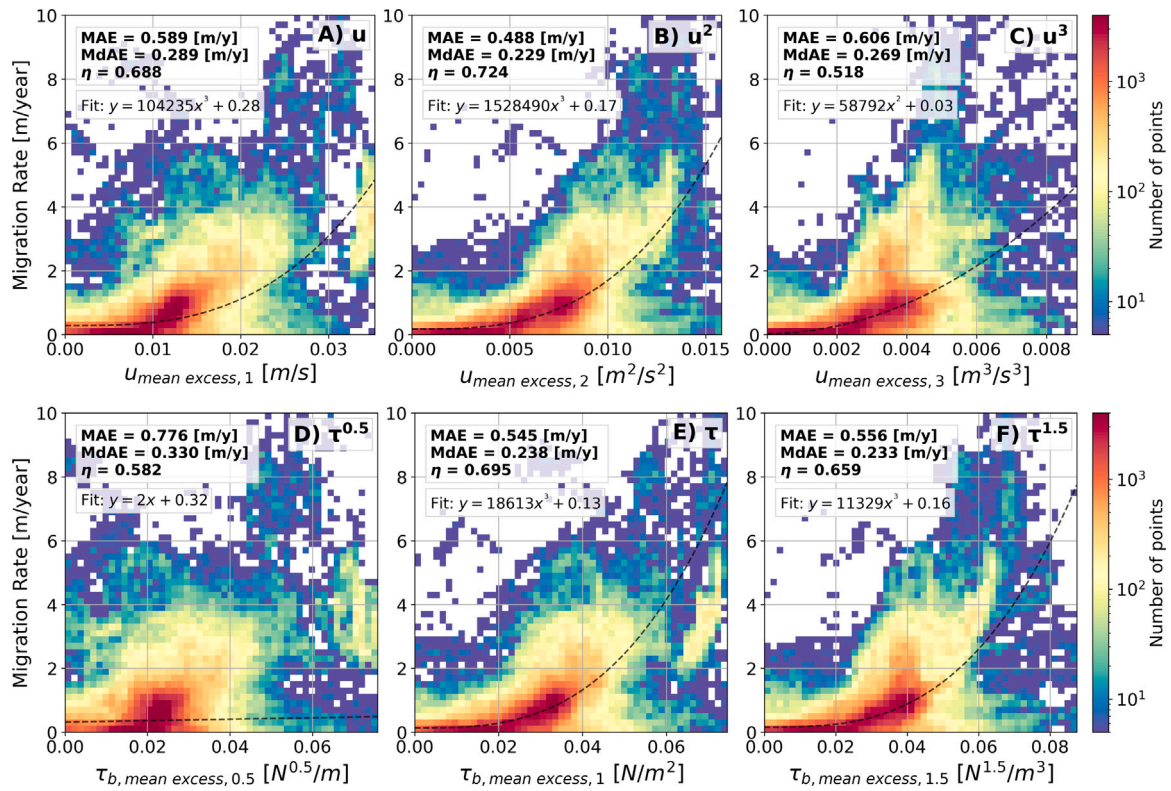


Fig. 9. Histogram of sand wave migration rate against the mean excess velocity, see Eq. (9) (A,B,C) and mean excess bed shear stress, see Eq. (8) (D,E,F) with different exponents, including a non-linear fit (dotted line). Additionally the Mean Absolute Error (MAE) and Median Absolute Error (MdAE) to this non-linear fit and the correlation ratio (η) are included.

Table 1. For $n = 1$, the threshold for motion is included but no non-linear scaling is applied when surpassing that threshold. For $n = 3$, the estimator becomes increasingly dominated by short periods of extreme mobility and more sensitive to uncertainties in critical velocity and roughness estimates, causing the relation with migration rate to deteriorate.

Similar behaviour can be seen for the mean excess bed shear stress shown in the lower plots of Fig. 9. Here also the highest migration rates show a relatively lowered excess bed shear, moving away from the non-linear fit, when a higher exponent ($n = 1.5$) is applied. Again, the Texel-Vlieland data still forms a somewhat separate group when the bed shear with exponents of 0.5 or 1 are considered, but moves towards the rest of the data for a higher exponent ($n = 1.5$). With a lower exponent ($n = 0.5$), the non-linear relation becomes somewhat unclear and based on MdAE optimization a gently sloping linear fit is found and performance of the estimator decreases. For the exponents 1 and 1.5 the non-linear estimators for migration rate based on excess bed shear have a MAE of around 0.55 m/year and a MdAE of around 0.23 m/year. This is in the same range as the velocity based approaches, although the MAE for the excess velocity with $n = 2$ is a bit lower.

The relationship between squared mean excess velocity ($n = 2$) and sand wave migration rate is promising. It shows a good match with the non-linear fit, similar behaviour across areas, and a clear connection with theoretical descriptions of sediment transport. Looking more closely to the different areas, we see that the relation is indeed more similar compared to the mean peak velocity difference, see Fig. 10. In the areas with low migration rates the highest point densities (darker areas) align quite nicely with the non-linear fit, sometimes showing a slightly lower migration rate than predicted. In the high migration rate areas (Brown Banks/turquoise, IJmuiden- Texel/lilac and Texel-Vlieland/red), the migration rate is slightly underpredicted by the fit. These are also the areas where the error statistics improve

most through the derivation of a local fit. Nevertheless, also in these areas the relation between the two variables does follow a similar non-linear trend. This is reflected by the lower coefficient of variation (CV) between the parameters (a and b) of different local non-linear fits ($y = ax^3 + b$). Relative to the mean peak velocity difference relations these coefficients of variation have lowered by over half and over two thirds for the a and b parameter respectively. Therefore, this variable shows promise for deriving the fit based on part of the data. Generally the areas with a higher average migration rate also show a larger spread from the non-linear fit, with the exception of the Zeeland Banks (yellow) and the IJmuiden-Maasvlakte (pink) areas, which show a large spread despite the low average migration rate. In these areas the most prominent underlying sand banks are found, which greatly influence the sand wave migration, see Fig. 2 and Fig. 4. Figures showing the spatial variation for the other estimators in Fig. 9 are included in the Supplementary Materials.

The improved consistency of the excess velocity estimator relative to the mean peak velocity difference indicates that migration rates are more closely related to asymmetry in sediment transport than to asymmetry in the hydrodynamic forcing itself. Locations with similar peak velocity differences may exhibit substantially different transport asymmetries due to variations in grain size, water depth, and mobility thresholds. Incorporating these thresholds therefore reduces regional differences and yields a more universal relation across the DCS.

3.3. Simplified sediment mobility: using a single sediment size

Since sediment data, which is used to calculate the local critical bed shear stress, is not always available, we will explore the sensitivity of our estimators to the sediment grain size. To this end we will apply a single median grain size for the calculation of the mean excess velocity across the DCS. For this grain size we chose 350 μm , which

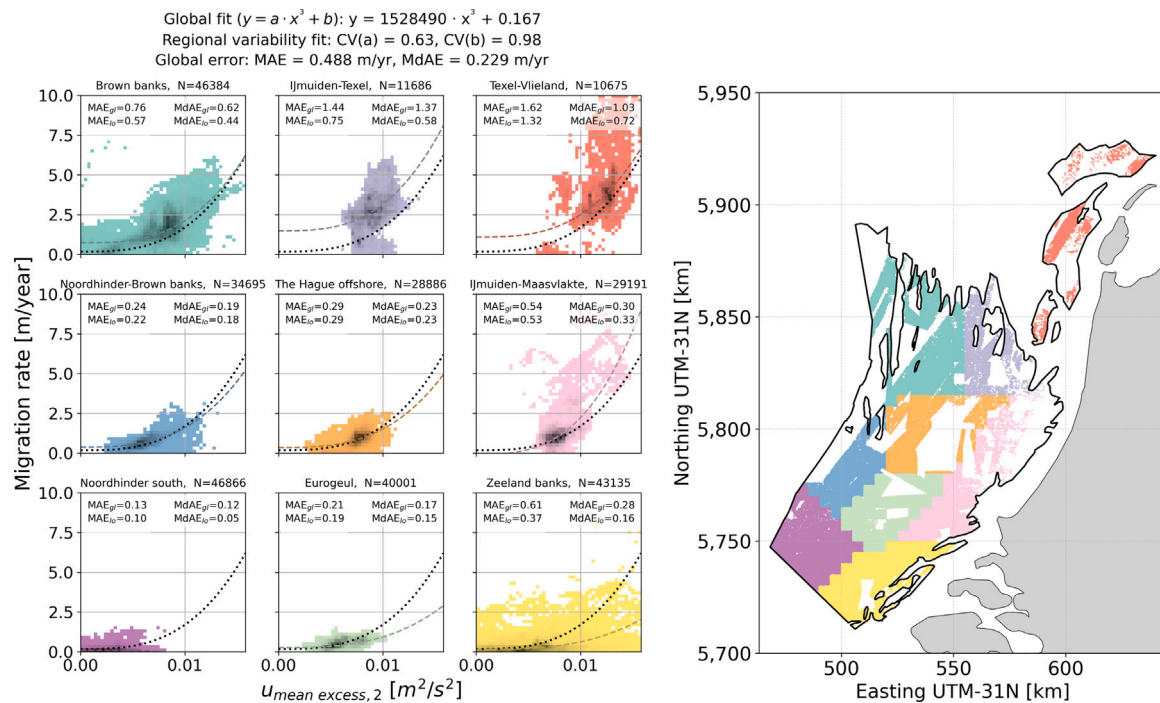


Fig. 10. Mean excess velocity with $n = 2$ (squared) from the run including meteorological forcing compared to sand wave migration rate per area including the global non-linear fit (black dotted line) and a local linear fit for that area (coloured dotted line). Darker areas show higher point density. Plot titles indicate number of points in the area (N). Within each plot the MAE and MdAE with the global (gl) and local (lo) linear fit.

is typical for sand wave areas on the DCS, see [Damen et al. \(2018\)](#), and close to the mean and median grain size of our dataset (359 and 357 μm respectively). By removing this variability, the critical depth averaged velocity is around 0.375 m/s (± 0.015 m/s depending on local water depth), where before it varied significantly from around 0.29 to 0.48 m/s.

From [Fig. 11](#) it is clear that even without detailed sediment data the relations between the hydrodynamic estimators (excess velocity and bed shear stress) and sand wave migration can still be found. However, the underestimation of high sand wave migration rates for higher order estimators becomes more prominent, see [Fig. 11 B, C and F](#). The areas with the highest migration rates in the North also have finer sand relative to the rest of the sand wave fields (with the exception of some specific areas near Texel and Vlieland), see [Fig. 2](#). There the critical bed shear stress is overestimated when using a single grain size throughout the DCS and this leads to an underestimation of the asymmetry in the excess velocity and bed shear. This underestimation gets amplified when a higher exponent is applied. This effect is less clear in the shear stress based predictors, since the shear stress is less sensitive to the exact critical value. The excess shear stress rises quicker when surpassing the critical value and shows less variation based on the exact critical value compared to the squared excess velocity, especially in the high mobility ranges. Therefore, the shear stress seems to be a better estimator when there is some uncertainty in the exact grain size.

4. Discussion

In this study we have shown the ability of local hydrodynamic conditions and sediment mobility to describe and explain sand wave migration rates on the Dutch Continental Shelf. The use of extensive datasets, with close to 300,000 verified sand wave migration data points, greatly improves the robustness of the estimators relative to previous studies. It is found that purely based on hydrodynamics a first estimation of migration rate can be made using the mean peak velocity difference. The obtained linear fit shows a MAE less than 0.5 m/year and a MdAE of less than 0.25 m/year with the full dataset. The

inclusion of non-tidal currents improves the ability of the fit to describe migration rates, especially for the less mobile sand waves. However, the relation between the mean peak velocity difference and the migration rates seems to vary significantly over the different regions of the DCS and does not display a non-linear relation as would be expected. By including the sediment mobility in the calculation, through the use of excess velocity and excess shear stress estimators (Eq. (9) and (10)) clearer non-linear relations are found with greater similarities over the different areas of the DCS. The most distinct relations are found using the excess velocity, but the excess shear stress shows higher robustness when sediment grain sizes are uncertain. Although the MAE and MdAE of these non-linear fits are marginally higher than that of the linear mean peak velocity difference fit, they do show greater promise for deriving overall estimators.

4.1. Survey inaccuracies and environmental conditions

Even for the improved estimators including sediment mobility, the spread in the data, and thereby the match with the non-linear fits, varies significantly between the areas. This spread could be caused both by inaccuracies in the determination of migration rates as well as missing processes on the side of the estimators. Especially in areas with low migration rates, the horizontal inaccuracies in the data (order of decimetres, depending on survey age) can complicate the determination of migration rates. For the shortest periods between measurements (~ 1 year), this directly translates in a migration rate error in the order of decimetres/year, although the migration rate data points are always averaged between different periods (including longer ones of 5–10 years), thereby reducing this survey error related uncertainty. Since the study by [Van der Meijden et al. \(2023\)](#) is largely based on the same data, the verification is unable to filter based on survey accuracy and only captures the inaccuracies due to the migration rate determination method. The variance based filtering is able to filter some data points based on expected survey or determination inaccuracies, but is applied rather conservatively to make sure data is not excluded based on natural variations in sand wave migration rate.

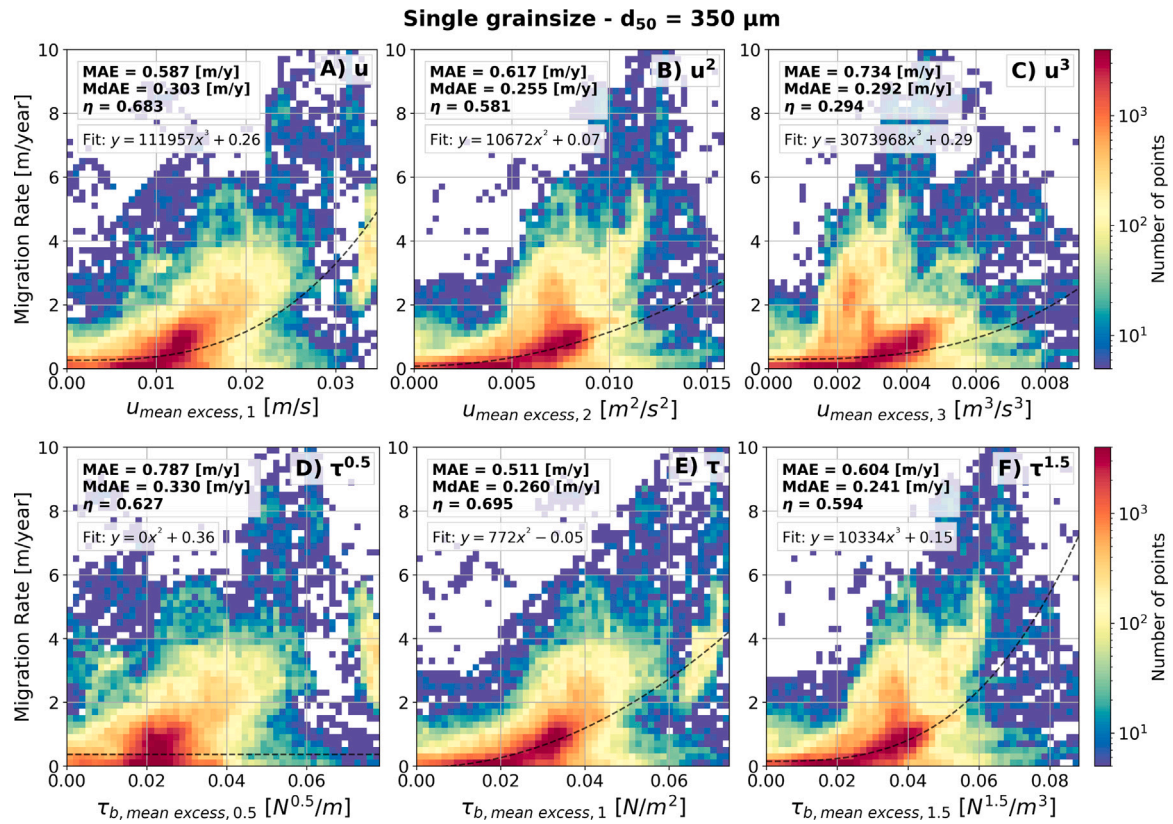


Fig. 11. Density plot of sand wave migration rate against the mean excess velocity, see Eq. (9) (A,B,C) and mean excess bed shear stress, see Eq. (10) (D,E,F) with different exponents, including a non-linear fit (dotted line). Additionally the Mean Absolute Error (MAE) and Median Absolute Error (MdAE) to this non-linear fit and the correlation ratio (η) are included.

From a process-based perspective it is interesting that the areas with a larger spread in the data (Brown banks, IJmuiden-Texel, Texel-Vlieland, IJmuiden-Maasvlakte and Zeeland banks) are those at the boundaries of the sand wave fields (the sand waves continue across the Dutch border into the UK and Belgium continental shelf). In the north and east, sand waves cease to exist under the combined influence of stronger hydrodynamic forcing and decreasing sediment size. These conditions promote suspended sediment transport, which can dampen sand wave growth (Borsje et al., 2014; Damen et al., 2018). These bordering conditions, with increased dominance of free surface waves and suspended sediment transport, could make it more difficult to estimate migration rates directly from hydrodynamic currents. However several other processes can also be identified which could explain a poorer match there.

Free surface waves can amplify the migration of sand waves, especially under extreme conditions (Campmans, 2018). However, at the DCS this effect is expected to be limited due to the significant water depths and limited free surface wave heights. Even for the 99th percentile extreme waves (derived by Damen et al. (2018)), these conditions are able to mobilize sediment at only 10% of our sand wave locations, and the median wave-related Shields parameter is 0.012 (approximately 1/4 of the critical value). Under normal conditions free surface waves are not expected to significantly affect sand wave dynamics (Campmans, 2018). Additionally, suspended sediment transport may increase migration rates (Van Gerwen et al., 2018), until suspended transport starts dominating over bed load transport (Rouse numbers < 2.5) which causes sand wave dampening (Damen et al., 2018; Borsje et al., 2014). Especially the particles in the lower part of the water column, still at times in contact with the bed, are expected to contribute to sand wave migration. These particles still act slightly like bed load transport and are affected by the excess velocity and excess shear included in the estimators. Therefore these effects may implicitly

be captured in the derived estimators. The suspended particles higher up in the water column, which only settle during calm conditions, are not expected to contribute much to migration, but rather have a dampening effect on sand waves.

The reasons for a poorer fit between excess velocity or shear stress and migration rate in some areas might be site-specific. Especially the Zeeland banks and IJmuiden-Maasvlakte areas stand out due to large scatter combined with low migration rates (Fig. 10). In both regions, underlying sand banks significantly influence local sand wave migration, with the highest rates occurring on bank crests. In IJmuiden-Maasvlakte, these high migration rates show the largest deviations from the fit. This indicates that the estimators underestimate sediment transport asymmetry on the bank. The mismatch decreases, however, when a higher velocity exponent is used. The Zeeland banks show more widespread issues with both under- and overestimation, possibly because the 2DH model has difficulty capturing the hydrodynamics surrounding the shallow banks or vertical processes like stratification play a role. The Texel-Vlieland area, which has the highest migration rates, shows the largest deviation (global fit MAE of 1.62 m/year and MdAE of 1.03 m/year). This area is particularly challenging due to high sediment heterogeneity (Fig. 2) and low sediment mobility, where peak velocities sometimes barely exceed critical values. Accurate determination of the critical velocity is therefore vital, but the heterogeneous sediment complicates this. Cheng et al. (2021) found significant variations (up to $100 \mu\text{m}$) in sediment grain size between crests and troughs of sand waves in this area. Determining representative local grain sizes from point measurements is thus difficult, especially since it is often uncertain what part of the sand wave the data is from. In such cases, using a representative overall grain size rather than questionable interpolations may be preferable and can still yield reasonable results (Fig. 11).

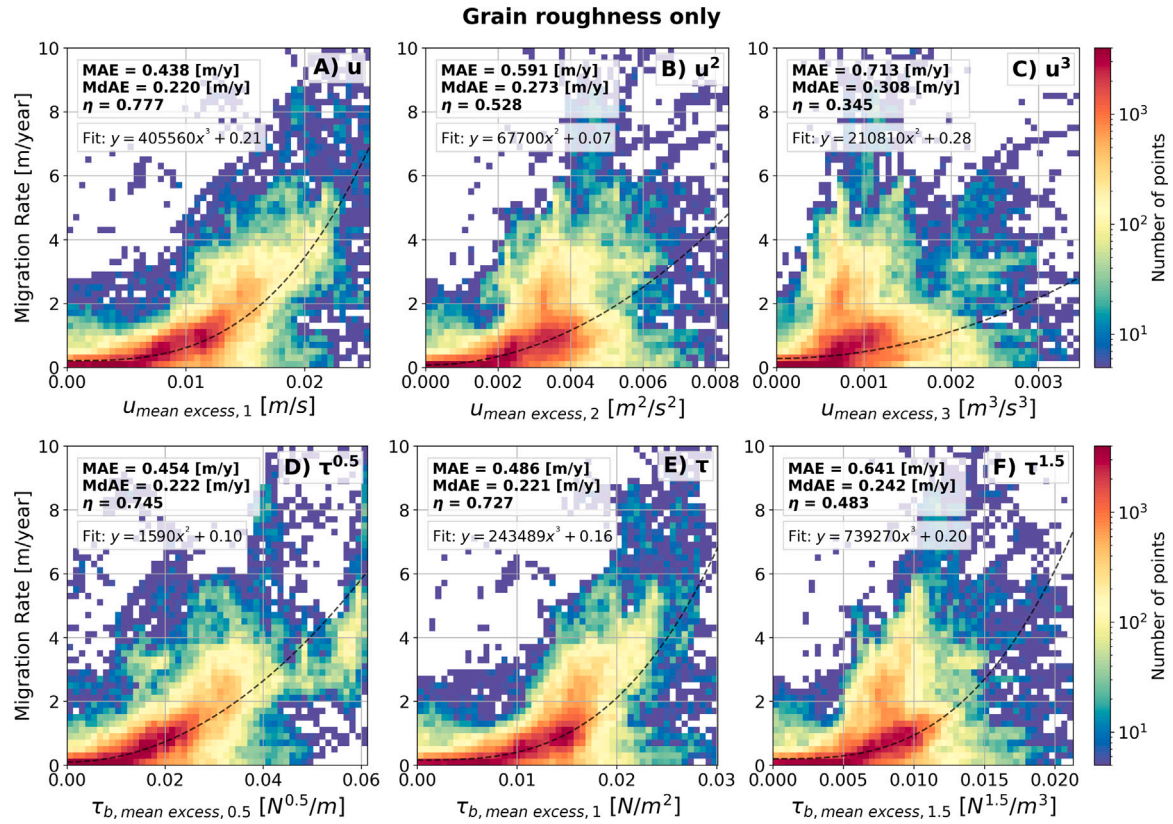


Fig. 12. Density plot of sand wave migration rate against the mean excess velocity, see Eq. (9) (A,B,C) and mean excess bed shear stress, see Eq. (8) (D,E,F) with different exponents, including a non-linear fit (dotted line). Additionally the Mean Absolute Error (MAE) and Median Absolute Error (MdAE) to this non-linear fit and the correlation (η) are included.

Finally, better representing bed roughness may be key to improving migration rate estimates. The bed roughness strongly influences the translation between bed shear stress and depth-averaged velocity. When bed roughness decreases, the critical depth-averaged velocity increases significantly for the same critical shear stress, and vice versa. An overly high critical velocity, due to low bed roughness, can significantly reduce the asymmetry in excess velocity and shear stress, since the ability of the currents to surpass the critical threshold is reduced. This effect intensifies with higher exponents, thereby explaining the poorer performance of $n = 3$ for the excess velocity and $n = 1.5$ for the excess shear stress. This is particularly relevant in low-mobility environments, such as Texel-Vlieland, where transport occurs close to the threshold of motion. To test this, the estimators were recalculated using only grain roughness ($k_s = d_{90} = 1.5d_{50}$). This option shows a promising fit with mean excess velocity ($n = 1$), achieving a MAE of 0.438 m/year and a MdAE of 0.222 m/year. However, adding an exponent to the excess velocity (or excess shear stress) to better represent sediment transport causes the fit to deteriorate rapidly (Fig. 12). Higher exponents underestimate the high migration rates in northern areas, a problem that was also observed with higher bed roughness, but is amplified when using only grain roughness. Future work should therefore focus on incorporating physical estimators or machine learning algorithms to improve the accuracy of the bed roughness estimations. This would enable spatially varying roughness based on sediment and flow characteristics, though estimating these variations at the scale of the DCS remains challenging.

4.2. Data bias and overfitting

To increase robustness of the results an extensive dataset is employed, including close to 300,000 sand wave data points. Still some bias could be present in the data, especially since all sand waves are

located on the DCS. The migration rates on the DCS are relatively low and steady compared to other areas. The dataset is therefore skewed towards less mobile sand waves and the drivers are mainly of tidal nature (although meteorological effects do play a role (Overes et al., 2024)). Therefore, these estimators should be tested in other areas where sand waves show higher migration rates (e.g. the Irish Sea (Van Landeghem et al., 2012)) or increased variability in migration over time (e.g. Harris (1991)). Since the sand wave migration on the DCS occurs steadily, the long-term average of the current or sediment mobility asymmetry is well able to describe this migration. However, in areas where migration is dominated by extreme events, for instance the sand waves on the Taiwan Shoal observed by Bao et al. (2020), directly linking the migration to these events may be more appropriate. Moreover, in these cases better matching of the hydrodynamic period with the measurement/prediction period or probabilistic assessment of hydrodynamics would be necessary. In this study, these periods did not match because of the large variation in survey dates. However, this was considered acceptable because migration is mainly driven by long-term asymmetry rather than by individual events. Finally, the DCS is characterized by an abundance of sediment. Since sediment scarce conditions could lead to increased bedform migration rates (Nnafie et al., 2023; van Veelen et al., 2024), the obtained estimators may need scaling before application in these environments.

Although biases may remain in the data, the size of the dataset significantly reduces the risk of overfitting. Overfitting is a realistic threat when deriving such estimators, as can be demonstrated by applying the migration rate predictor from Knaapen (2005), which was based on limited data from the same area. This predictor uses sand wave shape characteristics (asymmetry, height, and length) to predict migration rate and achieved a near-perfect fit with a correlation (R) of 0.98 and standard deviation of 0.34 m/year. However, despite measures to increase robustness, like including multiple locations and

separating calibration and validation datasets, only 4 of the 12 total data points contained sand waves with significant migration rates (> 0.5 m/year). Moreover, only one of these four data points ended up in the validation dataset, raising concerns about overfitting. To test this predictor on our dataset, we derived sand wave height, length, and asymmetry and verified these with data from [Damen et al. \(2018\)](#). While height matched well, length and asymmetry proved more sensitive and required filtering. We selected approximately 70,000 data points with maximum wavelength differences of 100 m and asymmetry differences of 0.2. Applying the predictor from [Knaapen \(2005\)](#) to this data yielded a weak correlation with a coefficient (R) of only 0.18 and a standard deviation of 6.8 m/year. This clearly shows that due to the limited dataset in the original study, the accuracy of the fit was greatly overestimated.

4.3. Migration rate vs. migration volume

It is often presumed that the net sediment transport rates from coarse resolution models, which do not resolve sand wave scales, can directly be linked to the migration-based volume transport of sand waves ($\approx$ migration rate $\times$ height). This hypothesis also relates to the belief that smaller sand waves migrate faster than neighbouring larger sand waves, since these have less volume to be transported. To verify whether instead of migration rates we should be focusing on migration volumes, we multiplied the migration rate with the sand wave height. In doing so the previously very clear relations with the hydrodynamic estimators (which resemble net sediment transport) disappeared (Figures included in Supplementary Materials). The migration volume even seems to be slightly negatively correlated to the estimators (higher migration volumes for lower asymmetry), which may be caused by the generally much larger height of the low mobility sand waves. Moreover, when comparing the height and migration rates of individual sand waves to those in their direct surrounding, no clear relations between sand wave height and migration rate were found (correlation ratio (η) of 0.1–0.2).

The absence of these relations shows us that sand wave migration volumes cannot directly be linked to the net sediment transport from coarse models. The momentary sediment transport from a coarse model probably resembles the average sediment transport over the sand wave. This transport rate is amplified at the crest and dampened at the trough locations, due to the interaction between the sand wave and the currents (see [Overes et al. \(2025\)](#)). The migration volume of the sand wave is then equal to the deposition from one tidal phase (flood/ebb), minus the erosion from the other tidal phase on one slope. The translation between sediment transport rate and sand wave migration volume is therefore not straight-forward. Moreover it could very well be that the amount of amplification and dampening of the sediment transport due to the sand wave bathymetry is related to the sand wave height. This could cause a higher variation in sediment transport rate for sand waves with greater height, thereby balancing the need for more deposition to achieve the same migration rate.

4.4. Practical implications and applicability ranges

The estimators found in this study show great promise for deriving overall relationships between hydrodynamic drivers and sand wave migration. Although they may still need tweaking in certain areas with different environmental conditions (e.g. wave-dominated or sediment-scarce), the fact that clear estimators, with MAE of less than 0.5 m/year, could be found is in itself remarkable. The robustness of these estimators is noteworthy given the uncertainties in migration rates (shape deformation and measurement uncertainty), hydrodynamics (2D approximations and differing time periods), and sediment transport thresholds (sediment size and roughness estimates). Despite these uncertainties, clear relationships remain visible. Their robustness was further demonstrated through the application of a single sediment size

and a different bed roughness (see [Figs. 11 and 12](#)). Still a MAE of 0.5 m/year could be judged as high, especially considering the on average low migration rates and increased error for more mobile sand waves. Therefore these estimators are especially valuable for deriving first-order estimates of migration rates, and have most added benefit in data-scarce areas, where other methods fail.

Although further validation, particularly in different environments, will improve confidence in these methods, the estimators can already be used to derive first-order migration rate estimates. In environments similar to the DCS (i.e., sediment-abundant, bed-load-dominated environments with low wave impact and slow, continuous migration), the estimators are expected to provide similar accuracy (MAE 0.2–1.5 m/year, MdAE 0.1–1 m/year, depending on magnitude of migration rates, data accuracy and process ambiguity). However, even in these areas it is recommended to use a benchmark to test their applicability. Even in data scarce areas often some overlap in the surveys is found, which can supply insights into sand wave migration rates locally. Using this data the estimators can be validated (and possibly tweaked) and then used to estimate migration rates in the surrounding areas. For areas with large uncertainty in sediment composition, bed shear stress estimators are recommended, although otherwise velocity based estimations may provide better accuracy. These sensitivities can also be tested using benchmark data. Without benchmarking it is expected that the estimators can only provide order of magnitude estimations (stable, low migration, high migration). However, even in these cases, the estimators can provide process-based insights into the drivers of sand wave dynamics. These insights can be used to estimate spatial and temporal variations in migration rates and their potential future development. For example, hydrodynamic time series with and without storms can be compared to estimate the relative contribution of different conditions. This approach can also provide insights into potential future changes, such as those associated with climate change. Application to areas with conditions that differ substantially from those of the Dutch Continental Shelf (e.g. wave- or storm-dominated environments, sediment-starved areas, or highly mobile seabeds) requires further research.

The greatest benefit of the estimators derived in this study is found in data-scarce areas where data-driven analysis is impossible. Even on the DCS, one of the world's most intensively monitored continental shelves, 900 km² of sand wave fields (7.5%) lack sufficient measurements to derive migration rates (from public datasets), while another 3000 km² (25%) has only two adequate measurements. In these areas and countless other data-limited regions worldwide, deriving sand wave migration directly from process-based estimators greatly enhances predictive capabilities. If there are no measurements available, it is immensely difficult, if not impossible, to make up for this, since measurement periods should span a sufficient time to ensure robustness. Even where ample measurements exist, the estimators derived in this study can improve migration estimates by revealing expected variability or enabling probabilistic predictions based on different hydrodynamic conditions and their occurrence probabilities. In these ways the derived estimators can greatly enhance our abilities to predict future bed levels in sand wave areas and thereby help prepare for the challenges ahead with the expansion of our offshore activities.

5. Conclusion

This study leverages extensive bathymetric, hydrodynamic, and sediment data from the Dutch Continental Shelf (DCS) to establish robust relationships between environmental forcing and sand wave migration rates. Analysis of nearly 300,000 verified data points, covering approximately 14,500 km of sand wave crests, shows that persistent tidal current asymmetry largely explains sand wave migration patterns on the DCS. Non-tidal currents can either enhance or dampen this asymmetry, particularly for slowly migrating sand waves, thereby improving the explanation of observed mobility and immobility. Including

sediment mobility through mean excess velocity and excess bed shear stress estimators reveals clearer non-linear relations that better capture the underlying physics of sediment transport. Moreover, these relations show greater consistency across different regions, although specifically in regions with underlying sand banks, the sand wave migration rates still show relatively large deviations from these fitted relations. The mean excess velocity with a second-order exponent showed a particularly promising match, with an MAE of approximately 0.5 m/year and an MdAE of approximately 0.25 m/year. The mean excess bed shear stress was more robust when sediment grain size was uncertain and showed good performance with $n = 1$. These exponent values lie within the range commonly used in sediment transport formulations and appear to provide a good balance between capturing non-linear transport behaviour and maintaining robustness to uncertainties in critical mobility thresholds.

These process-based relations advance both understanding and predictive capabilities of sand wave dynamics, enabling quick quantification of relative importance of different forcing mechanisms and insights into future dynamics under changing conditions. Beyond process insights, they provide first-order migration rate estimates even in data-scarce areas where data-driven approaches are impossible. The derived relations can be directly applied in regions similar to the DCS and, with further testing, potentially extended worldwide. Future work should focus on diverse environments with higher migration rates and more variable forcing conditions, enhancing our ability to predict future bed level dynamics and supporting safe, sustainable, and cost-effective offshore developments.

CRedit authorship contribution statement

Pauline H.P. Overes: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bas W. Borsje:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Arjen P. Luijendijk:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Ruben D. White:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Conceptualization. **Tom J. Roetert:** Writing – review & editing, Software, Methodology, Data curation, Conceptualization. **Suzanne J.M.H. Hulscher:** Writing – review & editing, Supervision, Project administration, 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.

Acknowledgements

This work was supported by the Dutch Ministry of Economic Affairs and Climate via the SITO-IS subsidy with Moonshot 4: Energy Transition at Deltares. In addition, the authors acknowledge NWO for funding this research through the Footprint project (project number: NWA.1236.18.003). Furthermore, the authors would like to acknowledge the Agentschap Maritieme Dienstverlening en Kust, Rijksdienst voor Ondernemend Nederland (RVO), the European Commission and DINoloket for providing the data for this study. Finally we want to thank the developers of the Delft3D FM software and the Dutch Continental Shelf Model, which was used for extracting hydrodynamics.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.geomorph.2026.110517>.

Data availability

The bathymetry data, used to determine sand wave migration rates, from the Dutch Hydrographic Office (NLHO) can be retrieved from [Deltares \(2017\)](#), high resolution data has to be requested directly from the Dutch Hydrographic Office (NLHO) via [Dutch Hydrographic Office \(2026\)](#). Bathymetric data from the Netherlands Enterprise Agency (within assigned windfarm zones) is available via [Netherlands Enterprise Agency \(2025\)](#). The large scale bathymetry data is available via EMODNET ([EMODnet, 2024](#)) and the sediment data can be retrieved from DINoloket ([DINoloket, 2007](#)). The processed data at sand wave crest points derived in this study (migration rates ([White et al., 2026](#)), sand wave characteristics, hydrodynamics, sediment mobility indicators), as well as comparison data from [Damen et al. \(2018\)](#) and [Van der Meijden et al. \(2023\)](#) is available via [Overes et al. \(2026\)](#).

References

- Bao, J., Cai, F., Shi, F., Wu, C., Zheng, Y., Lu, H., Sun, L., 2020. Morphodynamic response of sand waves in the Taiwan shoal to a passing tropical storm. *Mar. Geol.* (ISSN: 00253227) 426, <http://dx.doi.org/10.1016/j.margeo.2020.106196>.
- Besio, G., Blondeaux, P., Brocchini, M., Vittori, G., 2004. On the modeling of sand wave migration. *J. Geophys. Res. C: Ocean.* (ISSN: 01480227) 109 (4), <http://dx.doi.org/10.1029/2002JC001622>.
- Borsje, B.W., Kranenburg, W.M., Roos, P.C., Matthieu, J., Hulscher, S.J.M.H., 2014. The role of suspended load transport in the occurrence of tidal sand waves. *J. Geophys. Res.: Earth Surf.* (ISSN: 21699011) 119 (4), 701–716. <http://dx.doi.org/10.1002/2013JF002828>.
- Campmans, G.H.P., 2018. Modeling storm effects on sand wave dynamics (Ph.D. thesis). University of Twente, Enschede, The Netherlands, ISBN: 9789036546003, <http://dx.doi.org/10.3990/1.9789036546003>, Ph.D. thesis University of Twente. URL <http://purl.utwente.nl/doi/10.3990/1.9789036546003>.
- Cheng, C.H., De Smit, J.C., Fivash, G.S., Hulscher, S.J.M.H., Borsje, B.W., Soetaert, K., 2021. Sediment shell-content diminishes current-driven sand ripple development and migration. *Earth Surf. Dyn. Discuss.* 2021, 1–26. <http://dx.doi.org/10.5194/esurf-9-1335-2021>.
- Colebrook, C.F., White, C.M., 1937. Experiments with fluid friction in roughened pipes. *Proc. R. Soc. Lond. Ser. A-Math. Phys. Sci.* 161 (906), 367–381.
- Damen, J.M., van Dijk, T.A.G.P., Hulscher, S.J.M.H., 2018. Spatially varying environmental properties controlling observed sand wave morphology. *J. Geophys. Res.: Earth Surf.* 123 (2), 262–280. <http://dx.doi.org/10.1002/2017JF004322>.
- Damveld, J.H., Van der Reijden, K.J., Cheng, C., Koop, L., Haaksma, L.R., Walsh, C.A.J., Soetaert, K., Borsje, B.W., Govers, L.L., Roos, P.C., Olf, H., Hulscher, S.J.M.H., 2018. Video transects reveal that tidal sand waves affect the spatial distribution of benthic organisms and sand ripples. *Geophys. Res. Lett.* (ISSN: 19448007) 45 (21), 811–837. <http://dx.doi.org/10.1029/2018GL079858>.
- Deltares, 2016. Morphodynamics of Hollandse Kust (zuid) Wind Farm Zone. Tech. rep, Deltares.
- Deltares, 2017. Dataset documentation bathymetry NLHO. URL <https://publicwiki.deltares.nl/display/OET/Dataset+documentation+bathymetry+NLHO>.
- Deltares, 2020. Stromingsvalidatie Dieptegemiddelde Noordzee Modellen, Rapport 11203715-004-ZKS-0002-v0.2, Versie 1.0. Tech. rep, Deltares.
- Deltares, 2022. DCSM-FM 0.5nm: a sixth-generation model for the NW European Shelf. Tech. rep.
- Deltares, 2023. Morphodynamics for IJmuiden Ver Wind Farm Zone. WOZ2220017. Ref: 11208404-002-HYE-0001e. Tech. rep, Deltares, URL.
- DINoloket, 2007. Data en informatie van de nederlandse ondergrond. URL <https://www.dinoloket.nl>.
- Dong, P., 2015. Automated measurement of sand dune migration using multi-temporal lidar data and GIS. *Int. J. Remote Sens.* 36 (21), 5426–5447. <http://dx.doi.org/10.1080/01431161.2015.1093192>.
- Dorst, Leendert, 2009. Estimating sea floor dynamics in the Southern North Sea to improve bathymetric survey planning (Ph.D. thesis). University of Twente, <http://dx.doi.org/10.3990/1.9789036528788>.
- Draper, Norman R., Smith, Harry, 1998. *Applied regression analysis*, vol. 326, John Wiley & Sons.
- Dutch Hydrographic Office, 2026. Request hydrographic data. URL <https://www.defensie.nl/onderwerpen/hydrografie/distributie-zeekaarten-en-publicaties/aanvragen-hydrografische-data>.
- EMODnet, 2024. Emodnet digital bathymetry (DTM 2024). <http://dx.doi.org/10.12770/cf51df64-56f9-4a99-b1aa-36b8d7b743a1>, URL <https://emodnet.ec.europa.eu/en/>.
- European Commission, 2022. Offshore renewable energy. https://energy.ec.europa.eu/topics/renewable-energy/offshore-renewable-energy_en.
- Francken, F., Wartel, S., Parker, R., Taverniers, E., 2004. Factors influencing subaqueous dunes in the Scheldt Estuary. *Geo-Marine Lett.* 24 (1), 14–21.

- Fugro, 2016. Geophysical Site Investigation Survey Dutch Continental Shelf, North Sea. Tech. rep, Rijksdienst voor Ondernemend Nederland, URL.
- Harris, P.T., 1991. Reversal of subtidal dune asymmetries caused by seasonally reversing wind-driven currents in torres strait, northeastern Australia. *Cont. Shelf Res.* 11 (7), 655–662.
- Hulscher, S.J.M.H., 1996. Tidal-induced large-scale regular bed form patterns in a three-dimensional shallow water model. *J. Geophys. Res.: Ocean.* 101 (C9), 20727–20744. <http://dx.doi.org/10.1029/96JC01662>.
- International Hydrographic Organization, 2020. Standards for Hydrographic Surveys 6th edition. IHO publication No. 44. Tech. rep, International Hydrographic Organization, URL https://iho.int/uploads/user/pubs/standards/s-44/S-44_Edition_6.1.0.pdf.
- Knaapen, M.A.F., 2005. Sandwave migration predictor based on shape information. *J. Geophys. Res.: Earth Surf.* (ISSN: 21699011) 110 (4), <http://dx.doi.org/10.1029/2004JF000195>.
- Krabbendam, J., Nnafie, A., de Swart, H., Borsje, B., Perk, L., 2021. Modelling the past and future evolution of tidal sand waves. *J. Mar. Sci. Eng.* (ISSN: 2077-1312) 9 (10), 1071. <http://dx.doi.org/10.3390/jmse9101071>, URL <https://www.mdpi.com/2077-1312/9/10/1071>.
- Leenders, S., Damveld, J.H., Schouten, J., Hoekstra, R., Roetert, T.J., Borsje, B.W., 2021. Numerical modelling of the migration direction of tidal sand waves over sand banks. *Coast. Eng.* (ISSN: 03783839) 163, <http://dx.doi.org/10.1016/j.coastaleng.2020.103790>.
- Li, Yong, Lin, Mian, Jiang, Wen-bing, Fan, Feng-xin, 2011. Process control of the sand wave migration in beibu gulf of the south China sea. *J. Hydrodyn. Ser. B* 23 (4), 439–446. [http://dx.doi.org/10.1016/S1001-6058\(10\)60134-5](http://dx.doi.org/10.1016/S1001-6058(10)60134-5).
- Maljers, D., Gunnink, J., 2007. Interpolation of Measured Grain-Size Fractions. Tech. rep.
- Menninga, J., 2012. Analysis Of Variations in Characteristics of Sand Waves Observed in the Dutch Coastal Zone: a Field and Model Study. Tech. rep.
- Meyer-Peter, E., Müller, R., 1948. Formulas for bed-load transport. In: 2nd Meeting of the IAHR, Stockholm, Sweden.
- Németh, A.A., Hulscher, S.J.M.H., de Vriend, H.J., 2002. Modelling sand wave migration in shallow shelf seas. *Cont. Shelf Res.* 22 (18–19), 2795–2806. [http://dx.doi.org/10.1016/S0278-4343\(02\)00127-9](http://dx.doi.org/10.1016/S0278-4343(02)00127-9).
- Németh, A.A., Hulscher, S.J.M.H., De Vriend, H.J., 2003. Offshore sand wave dynamics, engineering problems and future solutions. Pipeline Gas J..
- Netherlands Enterprise Agency, 2025. Offshore wind bathymetry measurements. URL <https://offshorewind.rvo.nl/>.
- Nnafie, A., Krabbendam, J.M., de Swart, H.E., 2023. Consequences of limited sediment supply for long-term evolution of offshore tidal sand waves, a 3D model perspective. *Mar. Geol.* 464, 107148. <http://dx.doi.org/10.1016/j.margeo.2023.107148>.
- Overes, P.H.P., Borsje, B.W., Luijendijk, A.P., Hulscher, S.J.M.H., 2024. The importance of time-varying, non-tidal currents in modelling in-situ sand wave dynamics. *Coast. Eng.* 104480. <http://dx.doi.org/10.1016/j.coastaleng.2024.104480>.
- Overes, P.H.P., Borsje, B.W., Luijendijk, A.P., Hulscher, S.J.M.H., 2026. Data derived sand wave characteristics and migration rates and modelled hydrodynamics across the dutch continental shelf, underlying the publication: "estimating sand wave migration rates from in-situ hydro- and sediment dynamics". <http://dx.doi.org/10.4121/1c86e644-4ffd-4ab1-a28b-6b33a4c01c4f>.
- Overes, P.H.P., Borsje, B.W., Luijendijk, A.P., Reyns, J., Hulscher, S.J.M.H., 2025. The role of sediment transport processes in shaping offshore sand waves. *Cont. Shelf Res.* 105513. <http://dx.doi.org/10.1016/j.csr.2025.105513>.
- Ploeg, Wout, Roos, Pieter C, Borsje, Bas W, Hulscher, Suzanne JMH, 2025. Subsurface sediment properties and potential impacts of marine sand extraction on sand wave occurrence on the netherlands continental shelf. *Earth Surf. Process. Landf.* 50 (15), e70206. <http://dx.doi.org/10.1002/esp.70206>.
- Soulsby, R., 1997. Dynamics of Marine Sands. T. Telford London, UK.
- Van der Meijden, R., Damveld, J.H., Ecclestone, D.W., Van der Werf, J.J., Roos, P.C., 2023. Shelf-wide analyses of sand wave migration using GIS: A case study on the netherlands continental shelf. *Geomorphology* (ISSN: 0169555X) 424, <http://dx.doi.org/10.1016/j.geomorph.2022.108559>.
- Van Gerwen, W., Borsje, B.W., Damveld, J.H., Hulscher, S.J.M.H., 2018. Modelling the effect of suspended load transport and tidal asymmetry on the equilibrium tidal sand wave height. *Coast. Eng.* (ISSN: 03783839) 136, 56–64. <http://dx.doi.org/10.1016/j.coastaleng.2018.01.006>.
- Van Landeghem, K.J.J., Baas, J.H., Mitchell, N.C., Wilcockson, D., Wheeler, A., 2012. Reversed sediment wave migration in the irish sea, NW europe: A reappraisal of the validity of geometry-based predictive modelling and assumptions. *Mar. Geol.* 295, 95–112.
- Van Rijn, L.C., 1984. Sediment transport, part I: bed load transport. *J. Hydraul. Eng.* 110 (10), 1431–1456.
- Van Rijn, L.C., 1993. Principles of Sediment Transport in Rivers, Estuaries and Coastal Seas, vol. 1006, Aqua publications Amsterdam.
- Van Rijn, L.C., 2007. Unified view of sediment transport by currents and waves. I: Initiation of motion, bed roughness, and bed-load transport. *J. Hydraul. Eng.* 133 (6), 649–667.
- van Veelen, T.J., Roos, P.C., Hulscher, S.J.M.H., 2024. Modeling the cross-sectional dynamics of tidal sandbanks in sediment-scarce conditions. *J. Geophys. Res.: Earth Surf.* 129 (4), <http://dx.doi.org/10.1029/2023JF007308>, e2023JF007308.
- White, R., Roetert, T., Vermaas, T., 2026. A century of seabed morphodynamics: Data-driven sand wave evolution on the dutch continental shelf. In: Book of Abstracts of the Eighth International Conference on Marine and River Dune Dynamics. pp. 111–112.