Applications of airborne laser scanning for determining marine geoid and surface waves properties

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**ABSTRACT**

Marine and coastal applications require more than ever accurate and expansive understanding of the marine surface topography in the offshore domain, with the relationship of sea surface heights and geoid (equipotential surface of the Earth) being the key components. This study demonstrates some of the under-utilised and unexplored marine applications of airborne laser scanning (ALS) with respect to geoid heights verification and validation, as well as identification of surface waves properties. A synergistic methodology was developed that combines ALS measurements, hydrodynamic models and tide gauge records in conjunction with geoid models. Examination of the determined discrepancies with respect to the ALS-derived sea surface heights reveals concealed characteristics of the geoid and dynamic topography. A sea surface height accuracy of 1.7 cm in terms of standard deviation was achieved using a high-resolution regional geoid model. Furthermore, ALS point cloud data can be used to retrieve surface wavefield properties (waves heights, wavelengths and directions). In this study a direct method approach is presented. Such a deeper insight into the wave dynamics plays an enormous contribution in the understanding and quantification of coastal processes (erosion and sediment transport), as well as validation and calibration of wave models and relevant sensors.

**Introduction**

Although airborne laser scanning (ALS) is conventionally used for dry land topography mapping, it has potentially similar capabilities to provide accurate heights of liquid surfaces (e.g., Gruno et al., 2013; Zlinszky et al., 2014). Unfortunately, ALS’ full abilities for determining sea surface heights (SSH) and dynamic topography (DT) have so far been underutilised and unexplored (except for a few studies, e.g., Varbla et al., 2020a; Vrbancich et al., 2011). This has been partly influenced by the capital-intensive cost of performing ALS surveys (due to fully integrated hardware and aircraft requirements, e.g., Brock et al., 2002), as well as due to insufficient knowledge on the marine geoid. The recent introduction of less costly commercial portable ALS systems may complement the increasing demand for accurate (as good as 5 cm) and reliable SSH estimates from coastal and marine applications (e.g., engineering, navigation, research, climate change).

DT is defined as the SSH deviation from the marine geoid (i.e., DT = SSH – geoid) and represents one of the most useful parameters in terms of marine dynamics. Thus, knowledge of the marine geoid (i.e., the shape of the ocean surface under the influence of the gravity and rotation of the Earth alone) enables specification and quantification of oceanographic processes (e.g., sea level rise). Currently, many countries (e.g., Canada – Véronneau & Huang, 2016; USA – Li et al., 2016; National Geodetic Survey [NGS], 2013; the Baltic Sea region – Ågren et al., 2016; Ellmann et al., 2020) have implemented a gravity-based height reference datum, where instead of laborious geodetic leveling the redefinition of the national vertical datum is realised through geoid modelling. Such a high-resolution geoid model enables measurements of elevations and depths using existing and emerging global navigation satellite system (GNSS) technologies. We emphasise that these advances are of importance for the utilisation of ALS and its contribution to interdisciplinary research (hydrography, oceanography, geodesy, geophysics, climate research, etc.). Thus, the advances made in ALS technology and geoid modelling signify a necessity for a re-examination of the performance and utilisation of ALS, which may potentially be superior to other methods.

SSH and DT are usually captured by in-situ (GNSS, wave and tide gauges, e.g., Penna et al., 2018; Varbla et al., 2020b; Xu et al., 2016), remote sensing (satellite altimetry, e.g., Archer et al., 2020; Gómez-Enri et al., 2019; Vu et al., 2018) and hydrodynamic models (e.g., Liu & Huang, 2020; Madsen et al., 2019; Slobbe et al., 2013). Whilst most of these techniques represent SSH
and DT adequately, they often suffer from temporal and spatial resolution deficiencies, accuracy uncertainties and most importantly – undisclosed and overlooked variations in their vertical reference datums. For instance, satellite altimetry has coarse spatial and low temporal resolution (orbital cycles of satellite missions vary between 10–35 days). On approaching coastal areas, the satellite altimetry accuracy deteriorates due to approximations in atmospheric, sea state and geophysical corrections, as well as waveform distortions caused by coastal inhomogeneities (e.g., Cipollini et al., 2017; Vignudelli et al., 2019). Whilst modern tide gauges provide good (centimetre-level) accuracy with high temporal resolution (up to seconds), they are restricted spatially to the land bounded coastal locations. Contrarily, hydrodynamic models (HDMs) can derive DT with high spatial and temporal resolution. A major flaw of HDMs, however, is their unknown accuracy due to modelling set-up and associated errors (e.g., boundary conditions, forcings, parameterisations, etc.) and more so due to their arbitrary vertical reference datums (e.g., Jahanmard et al., 2021; Slobbe et al., 2013; Varbla et al., 2020a).

Instead, ALS systems are capable of high spatial resolution SSH monitoring for large areas within a short time frame. Accuracy of an aircraft mounted LiDAR (light detection and ranging) device that emits laser pulses and registers reflections from a land surface is usually estimated to be 5–15 cm (e.g., Huisings & Gomes Pereira, 1998; Van der Sande et al., 2010). Less reflective liquid surfaces (e.g., Höfle et al., 2009; Huang et al., 2012) are registered with a similar accuracy (Cocard et al., 2002; Gruno et al., 2013; Julge et al., 2014; Zlinszky et al., 2014) within near-nadir data corridor. The resulting vertical ranges are used to generate along-route 3D point clouds as opposed to SSH profiles provided by other methods (e.g., shipborne GNSS or satellite altimetry).

The ALS-measured instantaneous SSH can be used indirectly to derive many other datasets. For instance, geoid heights can be reckoned from SSH if DT is known from other sources. Such information is invaluable for the validation of marine geoid models, as conventional precise GNSS-levelling control points cannot be established offshore. This is especially important considering that accurate geoid models are needed to improve coastal mean DT estimates (Huang, 2017) and detect significant mean DT signals on smaller spatial scales that cannot be identified by utilising, e.g., global geopotential models (Idžanović et al., 2017).

Exploiting the advantages of different aforementioned techniques, this study demonstrates a method that combines oceanographic and geodetic approach to determine DT. The tide gauge derived DT is used to validate the HDM embedded DT and estimate the dynamic bias between the HDM and a vertical datum (see also Jahanmard et al., 2021; Varbla et al., 2020a, 2020b). Thus, the employed methodology allows not only the validation of geoid models, but also the determination of accurate DT and deficiencies in HDMs.

Besides the SSH low-frequency component (geoid and DT), LiDAR also allows the detection of smaller scale marine processes, e.g., surface waves. This has previously been conducted using a fast Fourier transform to obtain the wave number spectrum (e.g., Huang et al., 2012; Hwang et al., 2000) and by direct mapping of the sea surface (Vrbancich et al., 2011). Another direct method to determine sea surface geometry was hinted by Varbla et al. (2020a). Given the vast amount of 3D point cloud data a deeper exploration in terms of methodology and re-analysis is now performed. Such quantification of surface waves properties contributes vitally to the understanding of the coastal processes (e.g., erosion and sediment transport), sea state and extreme events, as well as for the validation of wave models. Currently, many coastal and marine applications still rely on wave data from discrete locations (e.g., wave gauges) that do not reflect the extensive wave dynamics (e.g., waves refraction, coupling, breaking). Thus, a practical case study is conducted to illustrate applicability of the developed method and the obtainable wavefield properties.

This paper thus examines some of the under-utilised and unexplored applications of using portable ALS systems: (i) accurate determination of the low-frequency component of instantaneous SSH that can be used for the validation of geoid models and examination of deficiencies in HDMs, and (ii) investigation of the high-frequency component to quantify the properties of surface waves.

**ALS measurements and synergy with hydrodynamic models**

**Background theory**

The ALS measured SSH (SSHALS) plays a crucial role in the geoid modelling result verifications, as well as in the HDM derived DT (DTHDM) evaluation with respect to a geoid model. The resulting discrepancies provide useful clues on the performance of HDMs and geoid signals/models in both spatial (for identifying problematic locations) and temporal (not dealt within the scope of this study) contexts. The HDMs, however, may possess a bias relative to a geodetic reference system (Jahanmard et al., 2021; Varbla et al., 2020a, 2020b). This dynamic bias has a low-frequency component that changes temporally and spatially (Lagemaa et al., 2011). The dynamic bias values

\[
DB(\phi^T_G, \lambda^T_G) = D_{T,HDM}(\phi^T_G, \lambda^T_G) - D_{T,CG}(\phi^T_G, \lambda^T_G)
\]
can be estimated at the locations of tide gauge stations with coordinates \((\phi_{i}^{TG}, \lambda_{i}^{TG})\), where \(DT_{TG}\) denotes tide gauge obtained DT and \(i\) time-instance of an ALS measurement. Due to its low-frequency nature, the dynamic bias at other locations \((\phi_{i}, \lambda_{i})\) can be assumed equal (within limited spatial domain) to the one at tide

**Figure 1.** Derivation of the ALS-based geoidal height \(N_{ALS}\). Notice that the depicted dynamic bias is negative (cf. Equation 1).

**Figure 2.** 10.05.2018 ALS campaign (numbers 1–7 signify the sequence of flight routes). Dotted isolines depict the NKG2015 geoid model (units in meters), whereby the bottom colour bar shows its discrepancies with respect to the ALS-based geoidal heights (see also Figure 3(f); the used HDM is HBM-EST). Coloured background shows uncorrected HBM-EST embedded DT (see the top colour bar) at 09:00 UTC. Red circles denote the employed tide gauges. The black and red arrows depict waves (height 0.7 m) and wind (speed 10.7 m/s) directions according to Suomenlahi aaltopippu wave station and Kalbådagrund meteorological station, respectively (during the 6th profile measurements at 09:30 UTC). Dashed lines depict the country borders.
gauge or estimated using, e.g., linear interpolation. The bias (DB) eliminated DT estimates combined with the SSH<sub>ALS</sub> provide then the marine geoid heights (N<sub>ALS</sub>; cf. Figure 1) as

\[ N_{ALS}(\varphi, \lambda) = SSH_{ALS}(\varphi_i, \lambda_i) - [DT_{HDM}(\varphi_i, \lambda_i) - DB(\varphi_i, \lambda_i)] \]  

(2)

An intercomparison between N<sub>ALS</sub> and geoid models (N<sub>Model</sub>) can now reveal abnormalities that may occur due to underestimated hydrodynamical processes in HDMs and/or geoid model errors as

\[ D(\varphi, \lambda) = N_{Model}(\varphi, \lambda) - N_{ALS}(\varphi, \lambda), \]  

(3)

where \( D \) is the discrepancy. As the marine geoid is usually only roughly known compared to on land (where precise GNSS-levelling control points are available and used for fitting gravimetric geoid models to the national vertical datum), the method allows identification of areas where further exploration may be required.

### ALS survey and data processing

A marine ALS survey was performed on 10.05.2018 in the Gulf of Finland (at the eastern section of the Baltic Sea located in the Northern Europe; Figure 2) within the frames of routine mapping of offshore islands. The Estonian Land Board’s survey plane Cessna Grand Caravan 208B mounted RIEGL VQ-1560i LiDAR Scanning System (operating at wavelength 1064 nm and pulse repetition rate 1 MHz) was employed. An operational flight altitude of around 1200 m yielded the width of the SSH data corridor ca 1000–1200 m and LiDAR footprint diameter 0.3 m, which is smaller than in most previous studies (e.g., Hwang et al.,

![Figure 3](image-url)  

**Figure 3.** Profile comparisons between (a) raw (uncorrected) HDM embedded DT<sub>HDM</sub>(\(\varphi_i, \lambda_i\)) and the estimated bias values DB(\(\varphi_i, \lambda_i\)), (b) corrected HDM data (Equation 2, the term within the square brackets), (c, d) EST-GEOID2017 and (e, f) NKG2015 validation results (Equation 3), whereas legends show the correspondingly applied DT corrections (no correction means that N<sub>ALS</sub> = SSH<sub>ALS</sub> in Equation 3). All comparisons consider 2875 data points; time is in UTC on 10.05.2018 (horizontal axes). Average and standard deviations of discrepancies are denoted by \( \mu \) and \( \sigma \), respectively.
The ALS measurements were acquired with a total flight time of approximately 1.2 hours that comprised of seven separate profiles (Figure 2).

The airborne GNSS and inertial measurement unit datasets were utilised for flight trajectory calculations with respect to the nearby Estonian national GNSS reference stations (Metsar et al., 2018). The RIEGL RiProcess software and standard workflow (e.g., Gruno et al., 2013) were used to compute 3D coordinate points that depict instantaneous SSH (with respect to the reference ellipsoid GRS-80). This massive point cloud dataset was further processed to obtain the low- and high-frequency (see Section “ALS-derived properties of surface waves”) SSH components. Although data quality is generally uniform, a systematic upward curve in data corridor edges (effect subsides generally inwards 300–400 m from an edge) was detected (Varbla, 2019). A likely cause is the scanner scale error (e.g., Kumari et al., 2011). To avoid error propagation to the results only the mid-corridor ALS data (50 m across-track from the nadir position to each side) was considered in the low-frequency SSH signal determination computations.

To determine the low-frequency component of the ALS-based SSH a 2D moving average low-pass filter was employed (method denoted as M1). The $1116 \times 100$ m (along- and across-track directions, respectively) filtering window length was defined to match the regional geoid models’ spatial resolution (0.01 × 0.02 arc-deg), whereby the filtering step (i.e., the distance between filtering windows centres; the windows overlap) was set 62 m (corresponding to aircraft’s average speed m/s). Filter windows are centred at the plane’s nadir and oriented along the trajectory. The processing resulted in 62 m resolution along-nadir height profiles ($SSH_{ALS}$), as well as standard deviation values and point cloud densities within the filter windows (the total length of profiles is 184.4 km). The corresponding average point cloud density is 6.2 p/m$^2$ (for the centre 100 m of the SSH data corridor, i.e., near-nadir point cloud density). If the 1000 m wide SSH data corridor is examined instead, the average point cloud density decreases to 2.9 p/m$^2$. This suggests that the pulse energy is reflected away from the LiDAR sensor more often at the SSH data corridor edges. Contrarily, the expected point cloud density over dry land with the used scanning system is 9.0 p/m$^2$ when using the same survey parameters.

**Dynamic topography data**

The utilisation of a HDM plays an imperative role in determining and comparing the offshore DT during the ALS survey. Two regional HDM models, HBM-EST (Estonian implementation of the HIROMB-BOOS model; http://emis.msi.ttu.ee/download/) and assimilated NEMO-Nordic, were employed. Both contain hourly DT data, whereby their spatial resolutions are 0.5 and 1.0 nautical miles, respectively (for details see Hordoïr et al., 2019; Lagemaa, 2012). Three nearby Estonian and two Finnish tide gauges (cf. Figure 2) were used to validate the HDMs and estimate dynamic bias between these and the EVRS (European Vertical Reference System) based Estonian national vertical datum EH2000. The Estonian tide gauges are pressure sensor equipped (Libusk et al., 2013) and rigorously connected into recently renovated national high-precision levelling network, whereby their zero values coincide with the geoid surface (Kollo & Ellmann, 2019). The tide gauge-derived DT is thus also referred to the geoid model. To make the Finnish tide gauge readings compatible a height conversion has been applied similarly to Kollo and Ellmann (2019).

Linear interpolation was used to grid (retaining the original HDM resolution) the dynamic bias estimates (Equation 1) over the study area (results are shown in Figure 3(a)). ALS-determined geometric marine geoid heights $N_{ALS}$ were then derived by combining the dynamic bias eliminated DT estimates (cf. Figure 3(b)) with the $SSH_{ALS}$ (Equation 2). The derived $N_{ALS}$ profiles were compared to the shipborne GNSS determined geometric geoid heights profiles presented in Varbla et al. (2020b). Note that DT for both ALS and shipborne GNSS based geoid heights profiles was estimated by using the HBM-EST HDM. The comparisons at 13 intersections yielded a standard deviation estimate of 3.3 cm and an average difference of 1.2 cm (the ALS profiles being higher than the shipborne GNSS-based ones), hence indicating good agreement and reinforcing thus the validity of the ALS data quality (and vice versa).

**Comparisons with geoid models**

Two regional high-resolution (both 0.01 × 0.02 arc-deg, i.e., approximately 0.6 nautical miles) quasi-geoid models EST-GEIOID2017 (Ellmann et al., 2020) and NKG2015 (Ägren et al., 2016) were validated and used to examine the HDM-derived DT by employing the ALS-determined marine geoid heights (Equation 3; note that over the marine areas the quasigeoid coincides with the geoid). The EST-GEIOID2017 is widely used by the Estonian surveying industry as the official national geoid model for converting the GNSS derived ellipsoidal heights into normal heights, whereas NKG2015 is used in the North-Europe countries. A comprehensive review of the models and comparisons between their surfaces are presented in Varbla et al. (2020b). The ALS-based validations (by considering 2875 data points altogether) are shown in
The applied methodology revealed several aspects with respect to the different sources of data, with the ALS results providing the only “true” in-situ source in the offshore domain. Firstly, the validation accuracies (in terms of standard deviation) are 1.7–1.8 cm and 3.9–4.1 cm for EST-GEOID2017 and NKG2015, respectively (Figure 3 sub-plots d and f). This suggests that an accuracy better than 5 cm can be achieved from the developed method. The significantly better performance of EST-GEOID2017 (by a factor of 2) is largely due to the inclusion of new shipborne marine gravity data in the southern half of the Gulf of Finland (acquired during a marine gravity campaign in July 2017) that are not considered in the NKG2015 computation (Varbla et al., 2020b). Roughly 1 dm geoid modelling improvement can be detected (compare Figure 3 sub-plots d and f at 08:50 UTC) in the profile 2 region (cf. Figure 2) where a gravity data void existed previously, thus emphasizing possibilities for better marine geoid modelling. Such ALS analysis can thus reveal poor performance areas of geoid models.

Secondly, the discrepancy comparisons of both quasigeoid models reveal similar negative gradients for profiles 1 and 3 towards shore and in the eastern half of profile 4 (cf. Figure 2, 3(d,f)). EST-GEOID2017 assessment with GNSS-leveling control points by Ellmann et al. (2020, Figure 8) supports this revelation (a control point close to the beginning of profile 1 reveals a ~0.8 cm discrepancy). This suggests aggravating impact of gravity data voids, as well as possible errors in the near coast gravity data and that geoid modelling can be further improved in the area. However, note that besides geoid modelling errors, such similar discrepancies between assessments may also indicate problematic areas in the HDMs. Hence, by utilising various geoid models more confident evaluations can be conducted.

Thirdly, the conducted assessments reveal the deficiencies of HDMs. It is obvious from the dynamic bias differences (see Figure 3(a)) that different reference datums are used for the HDMs’ compilation. The 3 dm dynamic bias of NEMO is significantly larger than the one of HBM-EST. Such a bias in offshore must be determined and removed for practical applications. On the contrary, the dynamic bias of NEMO appears to be less varying (significant variations over such a relatively small study area suggest HDM deficiencies) during the survey compared to HBM-EST. The ALS-based validation standard deviation improvements (e.g., 3.4 cm to 3.0 and 2.6 cm for HBM-EST and NEMO, respectively) by considering raw HDM data compared to no correction (i.e., \( N_{\text{ALS}} = \text{SSH}_{\text{ALS}} \)) in Equation 3 could suggest that NEMO is capable of deriving sea surface dynamics more accurately (cf. Figure 3 sub-plots c and e). However, a likely cause may also be in the models’ set-up differences. After bias removal (Figure 3(b)) the results are similar (Figure 3 sub-plots d and f). Whilst some identified discrepancies could be due to the geoid modelling, it would also be possible to identify HDM-caused discrepancies with a repeat ALS survey. The discrepancy variations between surveys could then reveal problematic areas that may need a closer look in compilation of future HDMs.

**ALS-derived properties of surface waves**

From the high-frequency component of raw ALS point cloud data the sea surface waves can be identified. Quantification of their properties has been performed using a 2D fast Fourier transform procedure (e.g., Huang et al., 2012; Hwang et al., 2000) or directly (Vrbancich et al., 2011). In this study a new direct method was developed (denoted as M2) to derive spatial distribution of surface waves properties, which were validated with in-situ wave gauge data (Figure 2). This method first involved a reconstruction of the raw instantaneous SSH as a 1 × 1 m resolution grids using an inverse distance weighted interpolation (a procedure that also reduces potential data noise). Secondly, wavelengths defined as horizontal distances between wave crests (defined as local maxima) were determined and constructed into 1 m resolution along-nadir profiles. Thirdly, wave heights were estimated as differences between along-nadir moving maximum and minimum filters with a 1 m step. The filters’ length (\( \xi \)) was defined as

\[
\xi(\varphi_i, \lambda_i) = 2\Lambda(\varphi_i, \lambda_i) + 1 + 2\Lambda(\varphi_i, \lambda_i),
\]

where \( \Lambda \) denotes the wavelength of the surface waves. The algorithm checks along-nadir SSH in a forward and backward direction two wavelengths each, but also considers that the wave crest or trough may occur to be at the current location with coordinates \((\varphi, \lambda)\) – this is denoted by the 1. The \( \xi \) was defined to be longer than the detected wavelengths (determined in step two) to avoid unrealistically low wave height estimates due to occasional overlapping waves, which resulted in shorter wavelength estimates as multiple wave crests were detected on a single wave (i.e., if \( \xi \) was defined shorter, on such occasions the determination of actual wave crests and troughs may have been unattainable). Although this also means that in other times multiple waves are considered simultaneously (i.e., when wavelengths are estimated correctly), it is assumed that there is no difference between the wave heights within such a short distance (note that the approach determines the highest wave within the filters’ length).
Finally, a moving average low-pass filter was applied to generalise the results (e.g., to filter out the estimated shorter wavelengths due to occasional overlapping waves). After removing outliers, a discrete sum of absolute differences function between filtered and reconstructed (step three) signals was first compiled for each profile separately. Maximum test filter length was always set to 2000 m (arbitrary estimate that was determined suitable during the compilation of the filter). Based on the sum of absolute differences function a new function was next compiled by using a three-point centred moving standard deviation. The final filter length was then defined as a value where the new function values reached first time 1/3 of its mean standard deviation. Such filtering resulted in reasonably smoothed wavelength and height profiles without changing the general trends (filter lengths were generally within 150–250 m). The computed wavelengths and heights are shown in Figure 4. High correlation ($r = 0.948$) between M1-derived standard deviation values and M2-derived wave heights reinforces the assumption of properly reconstructed instantaneous SSH.

During the ALS survey the majority of sea wavelengths varied between 5.9–10.2 m and heights 0.14–0.55 m (Figure 4), whereby higher waves were observed mostly in the NW section of the study area (profiles 5–7; cf. Figure 2). The general trend of these higher wave heights agrees well with the wave buoy (Suomenlahti aaltopoju) data of 0.7 m (cf. Figure 2). The $1 \times 1$ m data grids allowed also to estimate surface wind waves directions (not obtainable from wave gauges). Good agreement with the HDMs-embedded wind directions can be seen in Figure 4, whereas slight differences are expected due to the narrow shape of the Gulf of Finland (Pettersson et al., 2010). Notice that the HBM-EST-embedded wind data (Figure 4(a)) agrees better with both the meteorological stations measured wind and ALS-estimated waves directions than the NEMO model data (Figure 4(b)).

Figure 4. ALS-derived (a) wavelengths and (b) heights of the surface waves. The scaled grey vectors depict (a) HBM-EST and (b) NEMO HDMs embedded wind data (on 10.05.2018 at 09:00 UTC), whereas the scaled red arrows denote the actually measured wind data. The offshore black arrows (non-scaled) show ALS-estimated surface wind waves directions. Dashed black line depicts the Estonian marine border.
expected, Figure 4 also shows waves magnitude dependency on wind speed. Correlation coefficients between ALS-derived wave heights and HDM-embedded wind speeds from HBM-EST and NEMO are 0.846 and 0.795, respectively. Wavelengths, however, are not so well correlated with the HDMs-embedded wind speeds. The respective correlation coefficients are 0.647 and 0.584.

In addition to the wind-generated surface waves the ALS measurements also detected lower frequency swells on the background (Figure 5). A standard MATLAB signal processing low-pass filter was employed to extract the swells features from the ALS-measured sea surface (surface wind waves in Figure 5 were derived by subtracting the determined swell signal from the ALS measured combined signal). The filter’s sampling frequency of 62 Hz was defined according to the average speed of the aircraft (62 m/s) and the resolution of the used grids (1 × 1 m). As the ALS measurements result essentially in a snapshot of the sea surface, it is assumed that the used sampling frequency is constant in every direction with respect to the trajectory of the aircraft (i.e., the angle between the trajectory and the examined sea surface profile). It was then determined that a passband frequency of 0.5 Hz allows estimation of realistic swells features (this value roughly corresponds also to the estimated average wavelength of swells divided by the average speed of the aircraft). The derived wavelengths of swells agree well (within a few metres) with those measured directly from the computed grids. Also, notice good countability of swell crests (along the profile) from both the 3D sea surface model and the 2D graph in Figure 5. Wavelengths of the detected swells are generally 30–40 m with wave heights of 0.05–0.12 m.

The ALS measurements indicate a rather calm sea, whereby the sea surface was notably smooth in the eastern study area with wave heights mostly around or below 2 dm (Figure 4b). Earlier studies (Huang et al., 2012; Julge et al., 2014; Magalhaes et al., 2013; Zlinszky et al., 2014) indicate that such a smooth sea surface degrades the acquired ALS data.
Discussion and summary

ALS offers a significant capability for instantaneous and accurate SSH measurements especially in the off-shore domain, which introduces new possibilities for interdisciplinary research. Validation of different marine models (e.g., geoid and hydrodynamic models) and dynamics to identify problematic locations, as well as high-resolution mapping of the wavefield properties can be conducted. For instance, accurate spatio-temporal measurements of the wavefield (e.g., by combining geometry information and wave periods) could be used for the calibration of the wave radars and buoys, sea state parameters, and for the calibration and validation of wave models. Given the climate change effects on coastal areas (e.g., extreme events, flooding, coastal erosion) the contribution of ALS is expected to provide new insight and solutions. In addition, simultaneous satellite-derived and ALS-measured SSH and waves properties would allow to assess the satellite data quality.

Remember also that the developed method of this study has potential to reveal problematic areas and naturally occurring phenomena that are poorly described by the used HDM (i.e., discrepancies between the actual and modelled DT manifest as errors in the HDM-based DT). This can be done by conducting repeat ALS surveys, which would reveal both the reoccurring and time-variable discrepancies. Note that the geoid is a comparatively static surface, meaning that the reoccurring discrepancies likely describe the geoid model errors. The DT, on the other hand, varies in time. This suggests that the time-variable discrepancies could be caused by errors in the HDM that is used to describe the DT during the ALS survey. As certain HDM processes can be over-/under-estimated due to a particular model set-up, the method provides means to identify and quantify such problems. Hence, deeper examination is needed for ALS’ utilisation for many other purposes besides determining accurate SSH and surface waves.

Although ALS technology is still relatively expensive compared to some alternative sensors, national authorities are beginning to exploit ALS’ capabilities more frequently. A beneficial practice for the research community would hence be the distribution of ALS data over marine areas. Yet currently, ALS data is discarded, or the ALS system is turned off entirely over marine areas. The current study is a proof of concept that the research value SSH data can be acquired not only by specially designed ALS equipment but also by using standard ALS mapping routines and portable equipment. For instance, a portable ALS system could be mounted on aircrafts that are used for environmental and marine monitoring, e.g., for oil spills detection that are nowadays conducted regularly by various agencies. Potential future direction (e.g., for coastal monitoring) could also be unmanned aerial vehicle mounted LiDAR devices resulting in cheaper operational costs.

Acknowledgments

The research is supported by the Estonian Research Council grants “Development of an iterative approach for near-coast marine geoid modelling by using re-tracked satellite altimetry, in-situ and modelled data” [grant number PRG330] and “Wave dynamics for coastal engineering and management: the advantages and challenge of the Lagrangian perspective” [grant number PRG1129]. Grünthal, E. from the Estonian Land Board provided the coordinated ALS point clouds. Kaleva, L. from the Estonian Environmental Agency provided the used raw tide gauge data, which were then revised by Kollo, K. from the Estonian Land Board. A special thanks to the Swedish Meteorological and Hydrological Institute (SMHI) for their cooperation in obtaining NEMO-Nordic model data. The three anonymous reviewers are thanked for their contribution to the quality of the manuscript. The processed ALS data used in the study is made available through SEANOE data repository: https://doi.org/10.17882/76491.

Funding

This work was supported by the Estonian Research Council [PRG1129, PRG330].

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