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ABSTRACT
Across the oceans shorelines, monitoring the topography of the intertidal zone is generally challenging. The present study is motivated by the recognized role of the intertidal topography in the near-shore hydrodynamics. We consider the region of Chittagong (northern Bay of Bengal) because of its propensity to powerful cyclone surges and associated inundation hazard. So as to curb the lack of in situ knowledge of intertidal topography, we present an original procedure relying on spaceborne optical imagery. Our method essentially amounts to a water line detection performed at various tidal levels. We apply our procedure to the recent PROBA-V (Project for On-Board Autonomy-Vegetation) multi-spectral imagery mission. The first step of our procedure concerns the shoreline extraction. PROBA-V imagery consists of four bands (Red, Blue, near-infrared – NIR, short-wave infrared – SWIR), which are then combined to generate an artificial red-green-blue (RGB) image. This RGB image is then converted into the hue-saturation-value (HSV) colour space. A simple thresholding is applied to hue and value channels to separate water masses from land masses. This process is applied to several images taken at different water levels (i.e. different parts of the tidal cycle) and the corresponding water lines are inferred. To estimate the altitude level of the water lines, we rely on tidal observations from two gauges located at Chittagong and Cox’s Bazar. We operate an ad-hoc extrapolation of the point-wise gauge data to generate a synthetic tidal water level record all along the shoreline. These synthetic tidal heights are then combined with the shorelines to generate the final digital elevation model (DEM). The DEM we generated covers a 40-km long stretch of shoreline around Chittagong city. We assessed this DEM by comparison with two independent data sets based on in situ surveys as well as on Pléiades spaceborne stereoscopy. We conclude that our DEM is accurate within 1 m to 2 m, which is within the error bar of these validation data sets. Our procedure being essentially objective, it is easy to automate, for processing of other imagery satellite, including at high resolution and/or in real time.

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1. Introduction

The coastal strip of Bangladesh in the northern Bay of Bengal has a very low elevation, typically inferior to 4 m above mean sea level (MSL) over most of the Bengal delta (Krien et al. 2016). The coastal ocean shows a broad and very shallow shelf throughout the region, with water depth not exceeding 10 m in the first 50 km. This region is also characterized by a macrotidal regime, with tidal range in excess of 6 m–7 m. The climate of the region is characterized by a strong cyclonic activity during inter-monsoon seasons (spring and fall), with one major event every 3 years on average (Krien et al. 2017). These factors together make the shoreline of Bangladesh prone to surges and flooding (Ali 1996). The extreme population density of Bangladesh coastal districts (between 500 and 1500 per km\(^2\) on average, and much more in the urban centres), combined with the strength of the cyclone surges and floodings, make the area highly vulnerable (Begum 1996; Kay et al. 2015). The intense use of deltaic floodplains for agriculture, fisheries, and industrial production enhances their vulnerability (Islam 2016). One such hot spot of vulnerability is the megacity of Chittagong in south-eastern Bangladesh (Figure 1). The city is the major port terminal of the Bay of Bengal. It is the second largest city of Bangladesh, with an estimated 4 million inhabitants. Over the past few decades, a series of catastrophic cyclone events generated severe coastal flooding over Chittagong region. For instance, the 1991 event (24–30 April 1991, category 5 on the Saffir-Simpson scale) made landfall within 50 km of the city centre. It triggered a 6 m high surge that inundated most of the coastal side of the city and caused around 138,000 casualties. Thanks to preventive measures such as the large-scale construction of cyclone shelters and dykes, afforestation programs, early warning systems, and increased awareness among the people, the latest extreme events have been far less deadly. However, the whole sub-region still stands among the most vulnerable of our planet, in particular within the context of global sea level rise.

Modelling the dynamics of the storm surges is a major challenge for the scientific community. State-of-the-art numerical hydrodynamic models generally fail to reproduce the spatio-temporal evolution of the coastal flooding observed during these extreme events (Krien et al. 2017). Among the various factors limiting the performances of the numerical models is the improper knowledge of the near-shore bathymetry and land topography. Inaccurate representation of the bathymetry of the coastal strip severely impairs the realism of the tidal characteristics as well as surges and inundation patterns reproduced in these models hindcasts (Rose and Bhaskaran 2017; Krien et al. 2017). The issue of intertidal topography, in particular, has a strong impact on the wave set-up during storms and cyclones (e.g. Stockdon et al. 2006). Recently collected and digitized in situ hydrographic data over the Bengal shelf region significantly improved the skills of the numerical hydrodynamic models, in regard to the tidal characteristics (Krien et al. 2016). However, these data mostly consist of ship-borne point-wise soundings and leave the very shallow intertidal area essentially out of the surveys. Furthermore, the near-shore domain in this region is prone to marked morphological changes as a result of erosion and accretion processes, typically acting over a broad range of timescales (from days to decades). These changes result from the combined effects of sediment transports by the monsoonal runoff of the local rivers, tidal currents as well as by extreme hydrodynamic events such as floods and surges (Rahman, Dragoni, and El-Massari 2011;
This precludes a consistent, sustained monitoring through the sporadic and costly in situ hydrographic surveys that have been conducted over the area.

Here we present an alternative approach, relying on remote sensing multi-spectral data from the 100 m resolution of the 4 bands of the PROBA-V (Project for On-Board Autonomy-Vegetation) satellite (Dierckx et al. 2014) launched in 2013. To our knowledge, our present study is the first attempt to use this sensor to monitor the shoreline tidal variability. Besides its high quality in terms of geometry and radiometry (Sterckx et al. 2014), a distinct advantage of PROBA-V over other optical earth monitoring missions such as Landsat lies in its short revisit time (3 days) that allows collecting a large amount of cloud-free scenes in a short observation period. Indeed, the Bengal region is located in the core of the Indian monsoon region and is prone to frequent cloud cover, which makes spaceborne imagery of Earth surface challenging there (Rahman, Dragoni, and El-Massari 2011). Another advantage is its good enough resolution sensor (100 m) that allows capturing the km-scale migrations of the shoreline.

Figure 1. Geography of study area. The locations of the two tide gauges used subsequently are indicated with crosses. The background is a quasi-true-color synthesis from PROBA-V data on 11 March 2014.
position observed in our area over a tidal cycle. PROBA-V was recently used by Bertels, Smets, and Wolfs (2016) to investigate its capability to detect and delineate inland waterbodies at a global scale. They considered a coarser version of the satellite products (1 km to 333 m) along with a set of ancillary data products such as waterbody potential masks and volcanic soil masks.

The objectives of the present paper are twofold. First, we present an original, automated detection algorithm that processes the multi-spectral, highest-resolution (100 m) 5-day PROBA-V syntheses to infer the tidally driven migration of the shoreline in the Chittagong area. Then we relate these horizontal migrations to the tidal water height evolution, in order to translate them into a topography (elevation map) of the area they cover. The end-product of our study is a digital elevation model (DEM) of the intertidal area.

The intertidal region was identified as a challenging area, and essentially left out of the past remote sensing studies dedicated to water surface detection (Pekel et al. 2014). This is due to the frequent change of land cover (from water to soil and vice-versa) in this dynamic environment that precludes a routine, straightforward intercomparison/validation of spaceborne radiometric datasets of different sensors. A specific point of the present paper is to focus explicitly and solely on this intertidal area. Using spaceborne imagery to analyze the shoreline dynamics along the Bengal coast is not new, though. A few studies investigated the erosion and accretion signatures observed over multi-decadal timescales in the Sundarbans mangrove area (western Bengal delta) (Giri et al. 2007; Rahman, Dragoni, and El-Massari 2011). What is new here is the specific focus on the tidal imprint.

As previously noted, our target area, Chittagong and its surroundings, is a hot spot of coastal vulnerability in the Bay of Bengal (Begum 1996). It is also a relevant location for our case study, as the tidal range there is high relative to the beach slope. This results in a water line moving back and forth (shoreward/offshoreward) by several hundreds of meters or even several kilometers over a tidal cycle; such a range is a priori easily observable by the 100 m PROBA-V data. Apart from the tide, the shoreline position can vary under various other processes (such as cyclone surges, or erosion/accretion of the coastal sediments). These various processes act on different timescales. Here we consider the PROBA-V archive currently available over a 3-year period from 2014 to 2017. This duration is a good compromise in the sense that it is long enough to ensure a sufficient number of usable (i.e. cloud-free) scenes, and short enough to limit the influence of erosion/accretion on the topography of our area. This means that in the present study, we assume the bathymetry/topography of the intertidal area to be stationary in time, and that at any given location along the coastline a tidal height is univocally linked with one position of the land-water boundary. The 100 m resolution of PROBA-V data also allows us to discard the effect of the waves swash in the position of this boundary, as this process takes place at the sub-pixel scale. Inherently limited to cloud-free conditions, our data set also ensures that we are not prone to significant non-tidal surges of the water level, typically occurring when a tropical cyclone strikes the shore (which is invariably associated with cloudy sky).

One of our objectives is also to propose a robust detection algorithm, in the sense that its settings and performance should not depend on the variability of the optical properties of a given site. Our goal is that one can apply the algorithm routinely to the whole available archive of the sensor. Here, we apply our algorithm to PROBA-V data,
but we shall see that our algorithm is generic enough to be applied to other radiometric datasets with minimal adaptation.

2. Detection of the shoreline with PROBA-V data

2.1. Pre-processing of PROBA-V data

We consider the 5-day syntheses of multi-spectral radiometric data of VEGETATION instrument onboard PROBA-V (Dierckx et al. 2014). A sample of such a pentad synthesis is shown in Figure 2. We use the four spectral bands of VEGETATION instrument: blue (447–493 nm), red (610–690 nm), near-infrared (NIR, 777–893 nm) and short-wave infrared (SWIR, 1570–1650 nm), at 100 m resolution. All data files are already orthorectified, georeferenced, and corrected for optical and sensor errors (e.g. noise or distortions due to the lenses), atmospheric effects and cosmic rays. A 5-day synthesis basically consists of 1 to 3 individual swaths stitched together in one frame, with every pixel being associated with a date of observation. We considered 3 years of data, between March 2014 and May 2017. All images were visually inspected in our area of interest, to ensure that no massive clouds cover the coastal areas, and that no extended data gaps or bad exposure prevent the shoreline detection. From the 3-year archive, a subset of 16 best images were selected based on cloud cover, on the dates indicated in Table 1. This subset was found sufficient, as it covers practically the full tidal cycle (ranging from high tide to low tide), over our area.

Figure 2 reveals that the infrared bands (NIR and SWIR) capture particularly well the land/ocean transition, with water appearing very dark, and landmass appearing bright. This motivated us to consider SWIR band as a synthetic transparency band (traditionally termed as ‘alpha band’ in image processing) in the following. We considered the SWIR band preferably to the NIR band because the SWIR appears least affected by the sediments outflow seen in the northernmost part of Bay of Bengal, close to the mouth of the Meghna River (Figure 2). In NIR, the land/water contrast is not as prominent there.

Then, our approach essentially builds on the procedure of Bertels, Smets, and Wolfs (2016), except that we considered the highest resolution (100 m) PROBA-V syntheses (while they considered the 1 km and 333 m products only). The radiometric data are provided as byte arrays, in the range 0 to 255, for each band. In order to remove the effect of the changing illumination conditions among the records, we first applied a normalization to these data, to a value between 0 and 1 (0. being assigned to the weakest pixel of the scene, and 1. being assigned to the strongest pixel). This normalization was done for all four bands (blue, red, NIR, and SWIR), for each scene. We then converted the normalized data into a synthetic red-green-blue (RGB) space in order to take advantage of the land/sea contrast captured in the SWIR band, as follows:

\[
\begin{align*}
\text{red}_{\text{new}} &= (1 - \text{(SWIR)}_{\text{norm}}) + (\text{(SWIR)}_{\text{norm}} \cdot \text{(red)}_{\text{norm}}) \\
\text{green}_{\text{new}} &= (1 - \text{(SWIR)}_{\text{norm}}) + (\text{(SWIR)}_{\text{norm}} \cdot \text{(NIR)}_{\text{norm}}) \\
\text{blue}_{\text{new}} &= (1 - \text{(SWIR)}_{\text{norm}}) + (\text{(SWIR)}_{\text{norm}} \cdot \text{(blue)}_{\text{norm}})
\end{align*}
\]

where the subscript new refers to the newly generated bands, and the subscript norm refers to the normalized bands obtained from the VEGETATION native data.

Figure 3 shows the result of this conversion for the sample already presented. This conversion can be interpreted as a red, green, blue, and alpha (RGBa) to RGB conversion,
where the image is overlaid over a white background. The additional alpha band contains information about the transparency of a given pixel: the lower the alpha value, the higher the transparency. Here the SWIR band is used as the alpha band, as

Figure 2. Example of PROBA-V 5 day synthesis at 100 m resolution over our area for (a) red band, (b) near infra-red band (NIR), (c) blue band and (d) short-wave infra-red band (SWIR) (on 11 March 2014).

Table 1. List of dates of the PROBA-V images used.

<table>
<thead>
<tr>
<th>PROBA-V image acquisition date</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 March 2014</td>
</tr>
<tr>
<td>21 January 2015</td>
</tr>
<tr>
<td>26 January 2016</td>
</tr>
<tr>
<td>26 December 2016</td>
</tr>
<tr>
<td>26 October 2014</td>
</tr>
<tr>
<td>1 February 2015</td>
</tr>
<tr>
<td>11 January 2017</td>
</tr>
<tr>
<td>26 November 2014</td>
</tr>
<tr>
<td>6 March 2015</td>
</tr>
<tr>
<td>11 November 2016</td>
</tr>
<tr>
<td>6 January 2015</td>
</tr>
<tr>
<td>16 November 2015</td>
</tr>
<tr>
<td>11 December 2016</td>
</tr>
</tbody>
</table>
in SWIR water surfaces have a very low intensity (Figure 2 (d)), resulting in a very high transparency. Blending the RGBA composition with a white background results in water areas becoming nearly white, while the brightness of land surfaces (showing high intensity in SWIR band) remains practically unaffected. The red and blue band are included in the conversion because their resolution is higher than the NIR and SWIR bands in the native radiometric measurements of PROBA-V. The data of the NIR and SWIR bands are upscaled by PROBA-V pipeline so that their resolution matches the resolution of the red and blue bands data. This ensures that the smaller structures are retained in the composition, which would otherwise be blurry due to the upscaling of

Figure 3. Same as Figure 2, for the new colour space defined by Equation (1): (a) red band, (b) green band, (c) blue band, (d) red-green-blue (RGB) combined.
the NIR and SWIR bands. In the resulting synthetic RGB composition (Figure 3 (d)), water areas appear extremely bright, which will favour the identification of the shoreline.

### 2.2. Shoreline extraction

The basic principle of our shoreline detection procedure is to identify the border between water and land areas, i.e. between the white and green pixels in Figure 3 (d). This will be done by a thresholding approach. To determine the threshold, the synthetic RGB composition is converted into hue, saturation, and value (HSV) color space, following the same method as Pekel et al. (2014) (see their Equations (1)–(3)). In the rest of our study, only the hue and value will be considered. Figure 4 displays the hue and value images obtained for our sample. The rationale for designing our shoreline detection algorithm in the HSV space rather than in the RGB space is that hue is particularly sensitive to land cover change: typically a pixel covered with water at high tide and becoming dry at low tide (Pekel et al. 2014). Switching from RGB space to HSV space also results in a contrast normalization, which allows to use the same algorithm set-up to process various scenes with very different illumination conditions (which is bound to happen for a multi-year archive such as ours). Figure 5 shows the distribution of our data set in the hue-value domain. It is seen that two populations (blue versus red) are well separated, with points located in the offshore part of the ocean (in blue) restricted to low hue (below 180°)/high value (above 0.8), whereas remaining points (in red) mainly occur in the higher part of the hue domain only (above 200°). This clear separation allows us to convert our maps of hue and value to binary images, as follows. First, a gross, conservative, ocean mask is pre-defined once and for all by manual selection (Figure 6(a)). This mask covers the offshore ocean domain only, where the blue points of Figure 5 are located. The rationale for applying such a gross ocean mask, where the

Figure 4. Same as Figure 2, for the HSV synthetic colour space: (a) hue channel, (b) value channel. The greyscale for hue and value vary from 0 (white) to 1 (black).
near-shore ocean domain has also been removed, is to ensure we do not capture any land point. We apply this gross mask to the hue and value images, as illustrated in Figure 6(b,c) respectively, for our sample image. Since the ocean pixels appear more homogeneous than the land pixels in the value channel (Figure 4(b)), we apply this mask on the value channel. On the contrary, for hue channel, the land pixels appear more homogeneous than the ocean pixels, where the sediment-loaded river plumes are clearly visible; hence we apply the inverse of our mask to the hue channel.

Figure 5. Scatter plot of the hue and value channels obtained in PROBA-V dataset (restricted to three dates among those presented on Table 1, and plotting only one point every other 50, for clarity). Blue points fall within our ocean mask shown in Figure 6(a), red points fall out of it. Green points are the shoreline pixels subsequently identified by our algorithm.

Figure 6. (a) Gross water mask applied in our shoreline detection procedure. (b) Inverse masking of the hue channel, for our example of 11 March 2014. (c) Masking of the value channel on this date.
masked domain (for value channel) and on the inversely masked domain (for hue channel), we compute the median value and the standard deviation. These quantities are used for thresholding, as follows:

\[
BW_{\text{hue}}(i, j) = \neg ((l_{\text{hue}}(i, j) < T_{\text{hue}} + n_{\text{hue}} \sigma_{\text{hue}}) \land (l_{\text{hue}}(i, j) > T_{\text{hue}} - n_{\text{hue}} \sigma_{\text{hue}}))
\]  

(2)

\[
BW_{\text{value}}(i, j) = (l_{\text{value}}(i, j) < T_{\text{value}} + n_{\text{value}} \sigma_{\text{value}}) \land (l_{\text{value}}(i, j) > T_{\text{value}} - n_{\text{value}} \sigma_{\text{value}})
\]  

(3)

with \( \land \) being the regular AND-connection, \( \neg \) being the negation symbol, \( l_{\text{hue}} \) and \( l_{\text{value}} \) being the masked hue and value channels, \( BW_{\text{hue}} \) and \( BW_{\text{value}} \) being the resulting binary images, \( T \) and \( \sigma \) being the thresholds (median) and standard deviations, and \( n \) being the scaling factor of the standard deviation. The higher the scaling factor, the less strict is the thresholding. The scaling factors are kept constant for all images, which means that they have to be adjusted only once for a given data set/sensor, without the need to re-adjust for each individual image. In our case, after several trials, we fixed these parameters to 0.4 for \( n_{\text{hue}} \) and 5.0 for \( n_{\text{value}} \). The resulting binary maps obtained for our sample image are shown in Figure 7(a,b). The two binary images are then AND-connected, as follows:

\[
BW(i, j) = (BW)_{\text{hue}}(i, j) \land (BW)_{\text{value}}(i, j) \lor (OM)(i, j)
\]  

(4)

with \( \lor \) being the regular OR-connection, and \( OM \) being the ocean mask. The combined binary map \( BW \) obtained by this AND-connection is shown in Figure 7(c). As this image can contain some small-scale noise, all blobs with a size of less than 500 pixels are removed, as well as all holes with a size of less than 50 pixels. This cleanup is done automatically. The final step is to identify the shoreline from this clean binary map. This is done by convolution of the image with a 3 × 3 Laplacian kernel, as follows:

\[
M_S(i, j) = \sum_{p=1}^{3} \sum_{q=1}^{3} K(p, q) M_W(i - p + 1, j - q + 1)
\]  

(5)

with \( M_W \) being the clean binary map, \( M_S \) being the resulting shoreline map and \( K \) being the 2D kernel:

**Figure 7.** Binary maps resulting from our thresholding procedure, for (a) the hue channel, (b) the value channel, and (c) the combined channels, for the example of 11 March 2014.
\[ K = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \]  \hspace{1cm} (6)

This kernel is basically an edge detector. When applied on a binary image, it results in an image where only the pixels forming the edges are left. Figure 8 shows the resulting shoreline map for our sample case. Some minor post-processing is finally done to remove the artifacts that can appear during the various processing steps. In particular, for PROBA-V 5 day syntheses, we found that such artifacts occur sometimes on the edges of individual satellite swaths stitched together in one synthesis. This is done manually after the map generation.

Figure 9 illustrates the whole procedure with a flowchart. We applied the procedure routinely to all 16 images of our dataset and derived 16 different shoreline maps, each one corresponding to a different sea surface height of the tidal cycle. Figure 10 exemplifies three such shorelines obtained over Chittagong area for high tide, medium tide (i.e. close to MSL) and low tide conditions. It is clearly seen that the shoreline moves

**Figure 8.** Shoreline (blue) obtained at the end of our detection procedure, for the example of 11 March 2014. For visual purpose and clarity, note that the shoreline width was artificially increased to 9 pixels.
landward during rising tide, and seaward during ebb tide. The width of the intertidal area reaches its maximum at 22.3°N, with about 1500 m. This legitimates a posteriori the choice of our region, keeping in mind the 100 m resolution of our PROBA-V data set.

Now that we have defined the horizontal position (latitude, longitude) of the water line, the next step is to infer the elevation of this water line, all along its path.

Figure 9. Flowchart of our PROBA-V image processing procedure.
3. Inference of tidal conditions along the shoreline

In principle, assigning a vertical position to each pixel along the shoreline constructed in Section 2 is straightforward if, simultaneously to the satellite passes, a tide gauge monitors the temporal evolution of the water level in the region of interest. In practice, the tidal dynamics implies that the ocean surface cannot be considered as strictly horizontal over a very broad region, at any time. In other words, the tidal height evolution recorded by a tide gauge is representative of the sea surface height within typically a few kilometres around the tide gauge only. This is illustrated by Figure 11, which shows the evolution of the sea level observed during one week, both at Chittagong and Cox’s Bazar tide gauges. These observations were provided by the Intergovernmental Oceanographic Commission (IOC) Sea Level Monitoring Facility for Chittagong and by Bangladesh Inland Water Transport Authority for Cox’s Bazar. For Chittagong, hourly records are available from 2007 to 2017, hence encompassing entirely the period of our PROBA-V data set. For Cox’s Bazar, however, only one year of hourly data is available, from March 2014 to March 2015. The two sites are located 100 km apart (Figure 1). The one-week-long evolution displayed in Figure 11 (in mid-April 2014) is representative of the whole common period (not shown). It is seen that the two records bear some similarity, with a semi-diurnal dominant signal, and a spring-neap modulation of the amplitude of this semi-diurnal oscillation. Some differences also appear clearly between the two records. First, the amplitude of the semi-diurnal oscillation observed in Cox’s Bazar is consistently inferior to that observed at Chittagong. Also,
Chittagong evolution consistently lags behind Cox's Bazar. These differences stem from the known, deterministic propagation of the tidal waves in the North-Eastern Bay of Bengal: the tide propagates northward along the east coast of the Bay, and gets amplified during its propagation, with a maximum tidal range observed at the northern limit of the Bay, close to the mouth of the Meghna. The characteristics of this propagative pattern are known from hydrodynamical numerical tidal models, such as the one of Sindhu and Unnikrishnan (2013). Unfortunately, our region of interest, in the far-northern Bay of Bengal, is the area where state-of-the-art tidal models show the strongest errors. To our knowledge, the most realistic tidal model published over the region is that of Krien et al. (2016). In Chittagong for instance, it shows a typical error of about 20 cm. Further to the west, at the mouth of Meghna, this error amounts to about 40 cm. These errors are too high for us to be able to use directly Krien et al. (2016) model tidal heights to infer the vertical position of our PROBA-V shorelines. Rather, we will simply rely on Krien et al. (2016) model for the phase speed of the tide along its northward propagation, as well as for the relative increase in tidal amplitude from south to north along our coastline of interest. Figure 12 (a,b) displays the amplitude and phase of the tidal wave simulated by Krien et al. (2016) model in the northeastern Bay. For simplicity, we considered only the lunar semi-diurnal M2 tidal constituent, which dominates the tidal signal in the northern Bay (Sindhu and Unnikrishnan 2013). It is seen that the model amplitude increases by about 60% from south to north; as for the phase, it shows a lag

Figure 11. Sea level recorded by Chittagong (red) and Cox's Bazar (blue) tide gauges, from 10 April 2014 to 17 April 2014. The tidal level synthesized by our parametric model for Cox's Bazar over the same period is superimposed (green).
of about 60° (amounting to about 2 h) from Cox’s Bazar area to Chittagong area. Figure 12(c,d) shows the extraction of the modelled amplitudes and phases along our shoreline of interest. The northward increase of the model amplitude can be well approximated by a quadratic function (Figure 12(c)), whereas its tidal phase shows a linear shape. We will thus use these two simple analytical functions to extrapolate Chittagong observed tidal height all over our domain, throughout the PROBA-V period. The basic idea is to impose the two analytical functions to match exactly the amplitudes and phases of the tide observed at Chittagong and Cox’s Bazar gauges, over their 1 year long common period (March 2014 – March 2015). Doing so, we obtain a tidal evolution everywhere along our shoreline, based solely on Chittagong record. The behaviour of this simple parametric model is illustrated in Figure 11, for the specific case of Cox’s Bazar location (green curve). It is seen that it matches reasonably well the observed record there (blue curve), both in terms of amplitude and timing of the tidal evolution, day after day. Overall during the 1 year common period of Cox’s Bazar and Chittagong observations, we found that the standard error of our parametric estimate against the observed Cox’s Bazar record amounts to 14 cm. This is smaller than the typical error of

![Figure 12. (a) Amplitude (in m) and (b) phase (in °) of M2 tidal constituent from the hydrodynamic model of Krien et al. (2016) over the northern Bay of Bengal. Chittagong (red) and Cox’s Bazar (blue) are marked with crosses. (c) and (d) are extractions of (a) and (b) along the shore (extraction line shown in dashes on the maps). In (c), the amplitude has been normalized to the amplitude in Chittagong. The analytical fits of the extracted amplitude and phase are also displayed.](image-url)
Krien et al. (2016), and legitimates our simple approach. Cox’s Bazar being situated in the southern part of our region of primary interest (Chittagong surroundings), we can even expect lower error of our tidal estimates in the core of our region.

We use this parametric tidal estimate to assign an elevation to each pixel of our batch of detected PROBA-V shorelines, based on the time stamp provided with the images (at one minute accuracy) and the sea level observed at Chittagong tide gauge. These observations were referenced to their 2007–2017 long-term mean, so that the vertical reference of our elevations is also the long-term mean sea level.

4. Results

4.1. Our intertidal DEM

Figure 13 displays the DEM we obtain from the vertical referencing of our batch of PROBA-V shorelines, over Chittagong area. It is seen that our data set covers the major part of the tidal heights, with elevations ranging from $-2.25$ m to $+2.25$ m. Indeed, the observed tidal range is $\pm 2.50$ m in Chittagong. It is also seen that, in some instances, different contour lines appear to overlap. The reason for this is the similar tidal conditions sampled by our PROBA-V data set on different dates. Of course, this effect is more likely to occur where the terrain slope is steepest (as it is around 22.25°N for instance). Keeping in mind the resolution of our PROBA-V data set, as well as the typical resolution

![Figure 13. Structure of our DEM over Chittagong area. Elevations are referenced to mean sea level (in m). Positive upwards.](image-url)
of state-of-the-art hydrodynamical models used to simulate the coastal dynamics over our area (of order 100 m or coarser, see Krien et al. 2016), we decided to retain only three contour lines in our DEM for the subsequent analyses (namely the highest, the lowest, as well as the one closest to the mean sea level, at each latitude of our domain). This reduction limits the occurrences of overlapping contours such as seen in Figure 13.

4.2. Comparison with independent datasets

Because the potential sources of error in the elaboration of our DEM are multiple (radiometric errors in the PROBA-V images, geometric errors in the orthorectification/georeferencing of PROBA-V pipeline, errors in our shoreline detection algorithm, approximations in our simple parametric tidal model) and difficult to quantify a priori, it is needed to assess the realism of our product by direct comparison with independent data. This is not an easy task though, given the scarcity of in situ measurements in this critical zone, as stated in the introduction.

4.2.1. Comparison between our DEM and in situ soundings

This comparison relies on the two nautical charts from Bangladesh Navy Hydrographic and Oceanographic Centre covering our region of interest (chart #3001, based on surveys conducted in 2012–2013, and chart #3509, based on surveys conducted in 2014–2015). We considered all charts’ point-wise soundings falling in the intertidal area, digitized their locations, and co-located them with our own DEM. This resulted in 30 comparison points, displayed in Figure 14. It is seen that the two datasets present some significant differences, with a prominent shallow bias of our DEM compared to the soundings (the mean difference amounts to 1.2 m). Their standard difference is 1.5 m. These values are commensurate with the commonly accepted accuracy of in situ soundings (estimated to 1–2 m) (Sciortino 2010). This comparison gives strong confidence in our product and allows us to also conclude to an intrinsic accuracy of our DEM in the order of 1–2 m as well.

4.2.2. Comparison between our DEM and Pléiades DEM

In order to gain further confidence in our DEM, we considered an independent satellite-based product. This DEM was elaborated from a triplet of Pléiades images, acquired over our area on 11 May 2016. This stereoscopic triplet was processed to estimate a DEM of the area, following the method of de Franchis et al. (2014). As stereoscopy can provide only relative elevations, this DEM uses Earth Gravitational Model 1996 (EGM96) (Lemoine et al. 1998) geoid model to provide absolute elevations. The DEM accuracy is not known but is expected to be of order 2 m in terms of relative elevations (J. Michel, personal communication). As for the EGM96 geoid model, in this area where no recent ground measurements can be used to validate it, its accuracy is hard to establish. However, we can expect errors in the order of 0.2–0.4 m at the scale of a few dozens to hundreds of km (Pail et al. 2017). The DEM has a resolution of 0.7 m and is displayed in Figure 15. As the Pléiades pass took place while the tide was relatively low over Chittagong area, this DEM encompasses a fairly large fraction of the intertidal region (its upper half roughly). It was collocated with our own DEM by median filtering in the 100 m PROBA-V pixels. In contrast with the in situ soundings considered in the previous paragraph, our DEM
Figure 14. (a) Same as Figure 10, with the positions of the in situ sounding points superimposed (bullets). The bullets colours (pink-purple-blue) correspond to the magnitude of the difference between our DEM and the in situ soundings bathymetry. (b) Latitude-height plot of our DEM (green), of the in situ soundings (red), and of their difference (pink-purple-blue) (positive upwards).

Figure 15. (a) Comparison of our DEM with Pléiades DEM. The Pléiades DEM is shown in greyscale. The bullets show the positions of the overlapping pixels, and the colour (purple-pink) corresponds to the magnitude of the difference between our DEM and Pléiades DEM. (b) Latitude-height plot of our DEM (green), of Pléiades DEM (red), and of their difference (pink-purple-blue).
appears to be too deep compared to Pléiades DEM, on average. The match between our DEM and Pléiades DEM is significantly better in the northern part of our region of interest (north of 22.3°N). To the south of 22.3°N, Pléiades DEM shows consistently high elevations (between 1 m and 4 m typically) where our DEM is close to 0 m. The reason for this is unclear, and could be related to some extent to an improper filtering of the initial high-resolution Pléiades DEM (potentially contaminated by high elevation objects located in the near-shore strip, such as dikes, trees or buildings). Overall, the mean difference – standard difference between our DEM and Pléiades DEM amounts to –0.8 m–1.7 m, respectively. Although we can not consider Pléiades DEM as a reference product, the order of magnitude of these values confirms what we concluded when performing the comparisons with in situ soundings: our DEM is consistent with independent elevation products, to the extent of the known accuracy of these products.

5. Conclusion

The hydrodynamics and geodesy scientific community of the rim of the Bay of Bengal has been suffering from a lack of knowledge on the topography of the near-shore regions. This lack of information has been hampering our understanding and our capability to predict some fundamental natural processes such as the oceanic tide or the cyclonic storm surges and the associated coastal flooding events.

Here we present a procedure designed to provide an accurate estimate of the topography of the intertidal zone, based on the combination of spaceborne imagery and minimal in situ sea surface height records. In essence, our methodology amounts to an original procedure of water line detection. We apply this method to the multi-spectral radiometric data of the VEGETATION instrument onboard PROBA-V. With a comparison against in situ charts and Pleiades-derived DEM, we could conclude to an accuracy of our DEM in the order of 1 m–2 m over our area. However, the validation of our product is limited by the availability of independent in situ topographic/bathymetric observations. This calls for a specific high accuracy survey over our test area, through state-of-the-art techniques such as Global Navigation Satellite System (GNSS) and/or ship-borne multi-beam echo-sounding.

The distinct advantage of our method lies in its automated processing: the algorithm has to be tuned once and for all for a given sensor, and can be then applied routinely to the whole satellite archive without the need to calibrate it sample-by-sample. The only pre-requisite is to get access to at least one sea level record simultaneous to the spaceborne imagery data, over a given area. Experience shows that deploying an in-situ measurement device such as a tide-gauge station, and over a limited period of time, is much more tractable than carrying out bathymetric/topographic surveys over the whole intertidal area, over the several dozens of km of coastline stretch that can be covered with our approach. This is particularly true for remote places where access is difficult or restricted. This prospect is particularly interesting for regions such as the Bengal delta, where an in situ bathymetric/topographic survey is not easily feasible. Our approach is generic enough to be readily usable even without any in situ tidal measurements, on condition that an accurate tidal atlas exists over the area. This is typically the case for vast regions of the world coastlines, where state-of-the-art tidal models have an accuracy of order or better than 10 cm (Stammer et al. 2014). Our approach also has
promising potential for real-time monitoring of the shoreline morphology, in regions subject to erosion/accretion processes. Being computationally light, it is also suited to the upcoming generation of high-resolution radiometric sensors (such as the 2 m resolution Sentinel series, to be sustained for the next two to three decades), including for real-time applications.

Our dataset is freely available upon request to the corresponding author.

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Disclosure statement

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