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Role of benthic habitat distribution data in coastal water wind turbine site selection

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ABSTRACT

Environmentally concerned coastal zone management and marine spatial planning should minimize the risk of damaging sensitive benthic habitats. Since reliable maps of the underwater nature are scarce, planners often have to work with inconsistent data. We compare the outcomes of three hypothetical planning schemes with dissimilar input benthic ecology datasets in order to define suitable sites for shallow water wind turbine placement. The study is conducted in the northern Baltic Sea where the brown algae bladderwrack (*Fucus* spp.) forms important submerged habitats that can be disturbed by wind turbine construction. We evaluated the effects of the input data using two different approaches. In the first, we placed a maximum number of wind turbines at four different depth classes. After choosing the locations, we examined the potential area of affected *Fucus* habitats. In the second approach, we tested the accumulation of damage to *Fucus* habitats when adding new turbines to the research area by starting from the furthest available location of known important *Fucus* sites. Both approaches indicated that using data from airborne LIDAR helps coastal planners avoid the risk of unnecessary destruction of benthic key habitats. LIDAR surveys can help to optimize the locations for the detailed planning of vast areas in a way that point-based inventories or statistical predictive modeling cannot achieve.

1. Introduction

Environmentally concerned coastal development requires reliable information about the features, values and distributions of different shore habitats. Planning regulations often demand Environmental Impact Assessment surveys (EIA) to be conducted for new development projects. Finding reliable data to support spatial planning and EIA may be difficult since both the characteristics and distributions of ecologically significant submerged habitats, such as hard bottoms dominated by perennial algae or mussels are usually poorly documented. Specific subaquatic habitats can, for example, be important feeding or reproduction areas for marine life (Jackson et al., 2001; Kääriä et al., 1997), for which they should be given particular attention. The goal should be to optimize shore development in a way that enables societal aspirations with minimum damage to the most valued aspects of nature. This creates a necessity to distinguish between the areas of the highest conservation priority from those with lower significance. While a number of ecological considerations and value settings may occur, this demand also calls for reliable spatial data that can be used to describe and map the benthic nature (Barret et al., 2001; Jordan et al., 2005; Tammi and Kalliola, 2014).

Reliable data describing the underwater habitats are often scarce due to laborious and expensive field work. Although point data concerning biological values may be available from selected locations, the usefulness of such information in planning is limited if the areas in between remain undocumented. Decisions based on spatially inconsistent data may lead to undesirable situations, such as granting environmental permission to an activity that disturbs the seafloor in biologically sensitive locations. In order to avoid causing unnecessary environmental pressure, such deficiencies of spatial data should be minimized. One way is to use complementary data describing the abiotic environment, such as bathymetry, seafloor substrate or benthic illumination conditions to help identify the most likely locations for important habitats (Tolvanen and Kalliola, 2008). Additional information can also be gathered by the means of remote sensing, including aerial photographs (Barret et al., 2001; Ekebom and Erkkilä, 2003), satellite imagery

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(Mumby and Edwards, 2002; Phinn et al., 2008), multibeam sonar (Brown and Blondel, 2009), underwater video (Rinne et al., 2014) and SCUBA diving (Vahteri et al., 2000). In shallow waters, airborne bathymetric LIDAR (Light Detection and Ranging) is also a promising alternative, producing consistent data describing the benthic topography and habitats (Chust et al., 2010; Wang et al., 2007).

This paper examines how data from field inventories and LIDAR can contribute to coastal planning in a situation where human activities may threaten a benthic key habitat type. The development pressure to address in this article concerns a shallow water wind turbine construction in the northern Baltic Sea, where stands of the brown algae bladderwrack (*Fucus* spp.) provide shelter and food for many coastal species (Kautsky et al., 1992; Kraufvelin and Salovius, 2004). Our specific research question is whether the use of data from field inventories and LIDAR improves the possibilities to find suitable places for possible wind turbine locations and at the same time, to help avoid environmental damage.

2. Materials and methods

2.1. Study area

The Baltic Sea is the world's second largest brackish water basin. It borders on nine countries and has a population of around 85 million people within its drainage area. Human activities are intensive throughout the regions' coastal zone (HELCOM, 2010). Our study area is the Rönnskären archipelago in the northern part of the Baltic Sea in the Gulf of Bothnia, approximately 40 km from the city of Vaasa (Fig. 1). In this region, the coast is characterized by a complex shoreline, shallow waters (mainly less than 50 m in depth) and a multitude of islands of varying sizes. Coastal lagoons and shallow areas characterized by rocks and boulders harbor the highest biodiversity in the area. The benthic vegetation varies from extensive stands of *Fucus*-dominated areas in mainly wave exposed sites to muddy seabed with vascular plants in sheltered areas. *Fucus* is abundant in the Gulf of Bothnia and one of the most notable species in the area. Although benthic vegetation occurs down to a maximum depth of 10–12 m, the vegetative biomass generally declines at around 6–7 m. The annual Secchi depth in the study area varies from 3 to 6 m.

The exact delineation of the study area was determined by LIDAR data availability, comprising two separate, somewhat parallel blocks close to each other with a combined area of about 42 km^2. These areas constitute parts of a HELCOM (Helsinki Commission) Baltic Sea Protected Area, a Ramsar site and a Natura 2000 network. Parts of the study area also belong to the Kvarken Archipelago World Heritage site (http://www.kvarkenworldheritage.fi/visit-kvarken/). Both the geology (Breilin et al., 2005) and the benthic habitats of the study area are well inventoried, the latter by the Finnish Inventory Program for the Underwater Marine Environment (VELMU program, see Downie et al., 2013; Rinne et al., 2011). Good data availability makes this study area particularly suitable for the present work, where wind power construction is addressed as a theoretical case which may interfere with sensitive benthic nature.

There are some large-scale plans for offshore wind power development ongoing near the areas covered by this study. For this reason, reliable environmental data and knowledge is needed. However, the research area in itself cannot be used for wind turbine construction because of its protection status.

2.2. Data sources

For bathymetry, we applied both a conventionally used robust model, called 'bathymetry-C' (based on interpolated sea chart data with a pixel size of 20 × 20 m), as well as a LIDAR-enhanced model,

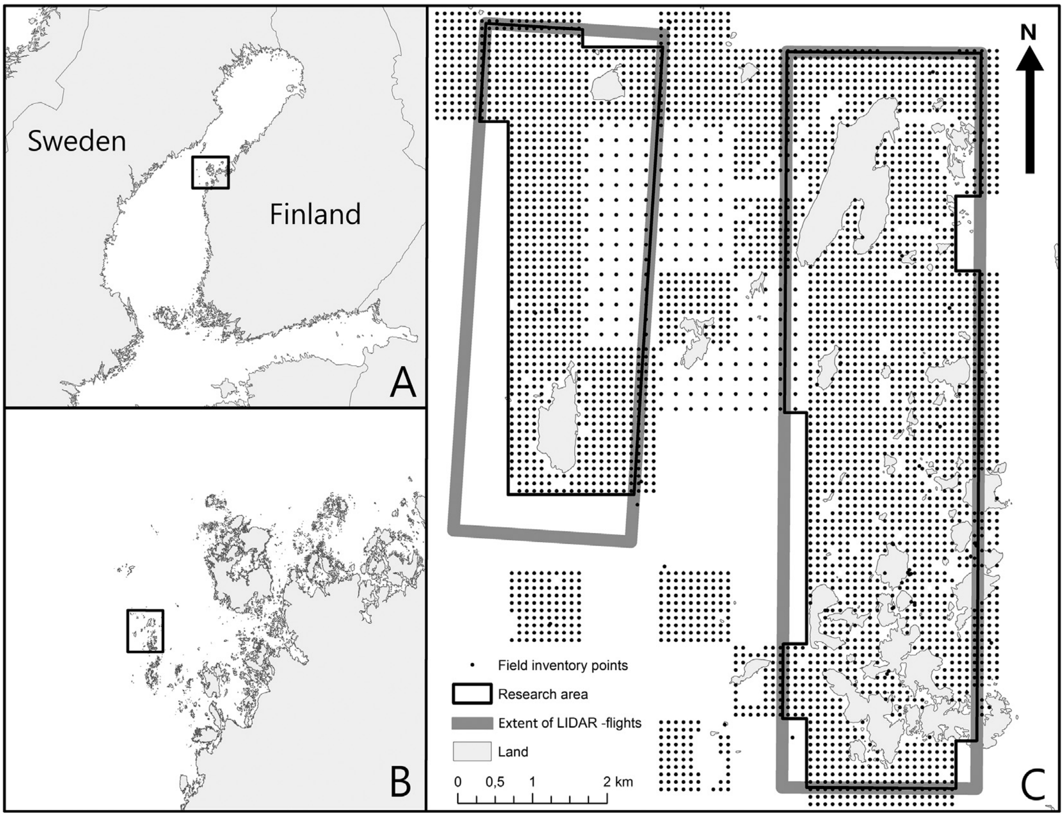

Fig. 1. A. and B. Location and of the study area. C. Coverage of the LIDAR data (areas bordered by grey outline) and underwater inventory points (black dots), and delineation of the research area in this paper (black outline).

'bathymetry-L', where shallow water areas (less than *ca.* 13 m) were mapped with airborne LIDAR and have a pixel size of 0.5 × 0.5 m (Fig. 2). The former data is available for planners from any part of the Finnish coast and it has been commonly used in environmental planning. However, it is spatially inaccurate in shallow waters at local scales. The latter data (bathymetry-L) was captured in September of 2009 from 200 to 450 m altitude by a field campaign of the Botnia-Atlantica Interreg projects ULTRA (Development of LiDAR -based Terrain analysis for Regional Use) and SUPERB (Standardized Development of Planning and Ecological Tools for the Bothnian Bay) (http://ultra-superb.eu/index.php/ladda-ner/lidar). Although it gives a highly detailed picture of the bottom topography, it is only available from the areas shown in Fig. 1C (http://ultra-superb.eu/index.php/ladda-ner/lidar). LIDAR data was registered using the HawkEye II survey system, where infrared laser pulses reflect from the water surface and green pulses reflect from the sea bottom, enabling the computing of sea floor topography based on the time lapse between the surface and bottom reflection. LIDAR is suitable for bathymetric mapping up to 2.5–3 times the Secchi depth (Gao, 2009) (Fig. 3).

Data on the distributions of the *Fucus*-dominated habitats were taken from two different sources. The first, i.e. '*Fucus*-I' utilizes data from point-based drop video inventories of the VELMU program, each covering some 20 m^2 of seabed. The study area contains 3046 inventory points, which are located 100 × 100 m or 200 × 200 m apart (see Fig. 1C and Fig. 2C). Each inventory point was surrounded with a buffer of 200 m and classified as an important *Fucus* area if the inventory point had *Fucus* coverage >25%. By comparison, the dataset '*Fucus*-L' results from the waveform variables of the returning laser pulse of the LIDAR data. The classification was based on the method that is described by Tulldahl and Wikström (2012) and has a tested accuracy of 79% in the research area. Patches with >100 m^2 of continuous *Fucus* coverage in the LIDAR data were defined as important *Fucus* areas and were furthermore surrounded with a buffer of 200 m.

2.3. Data analysis

The study design compared three different planning schemes for wind turbine placement. The 'conventional planning scheme' used the dataset bathymetry-C and had no data concerning *Fucus*; the 'inventory assisted planning scheme' applied bathymetry-C and *Fucus*-I; and the 'LIDAR assisted planning scheme' utilized bathymetry-L and *Fucus*-L. Each turbine was surrounded with a buffer with a radius of 200 m and the environmental impact was assessed according to its overlap with *Fucus*-L distribution data (Fig. 4). All the spatial analyses were made using GIS (Geographical Information System) using ArcMap 10.1 software.

We applied two different approaches to compare the three alternative planning schemes. Approach 1 aimed to define a

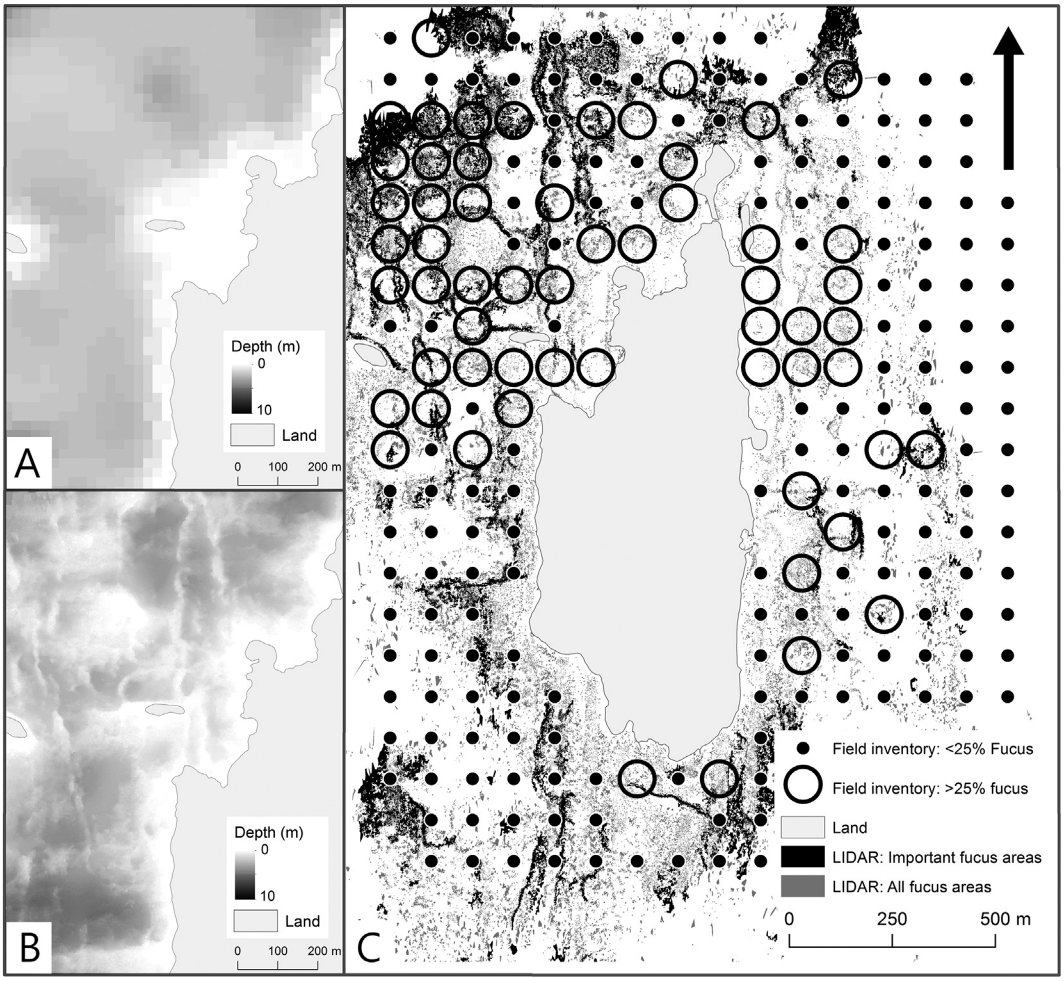

Fig. 2. Examples of the different data sets used in this study. A. Bathymetry-C. B. Bathymetry-L. C. Fucus-I with the two different coverage classes, and Fucus-L based on airborne LIDAR with the two different density classes.

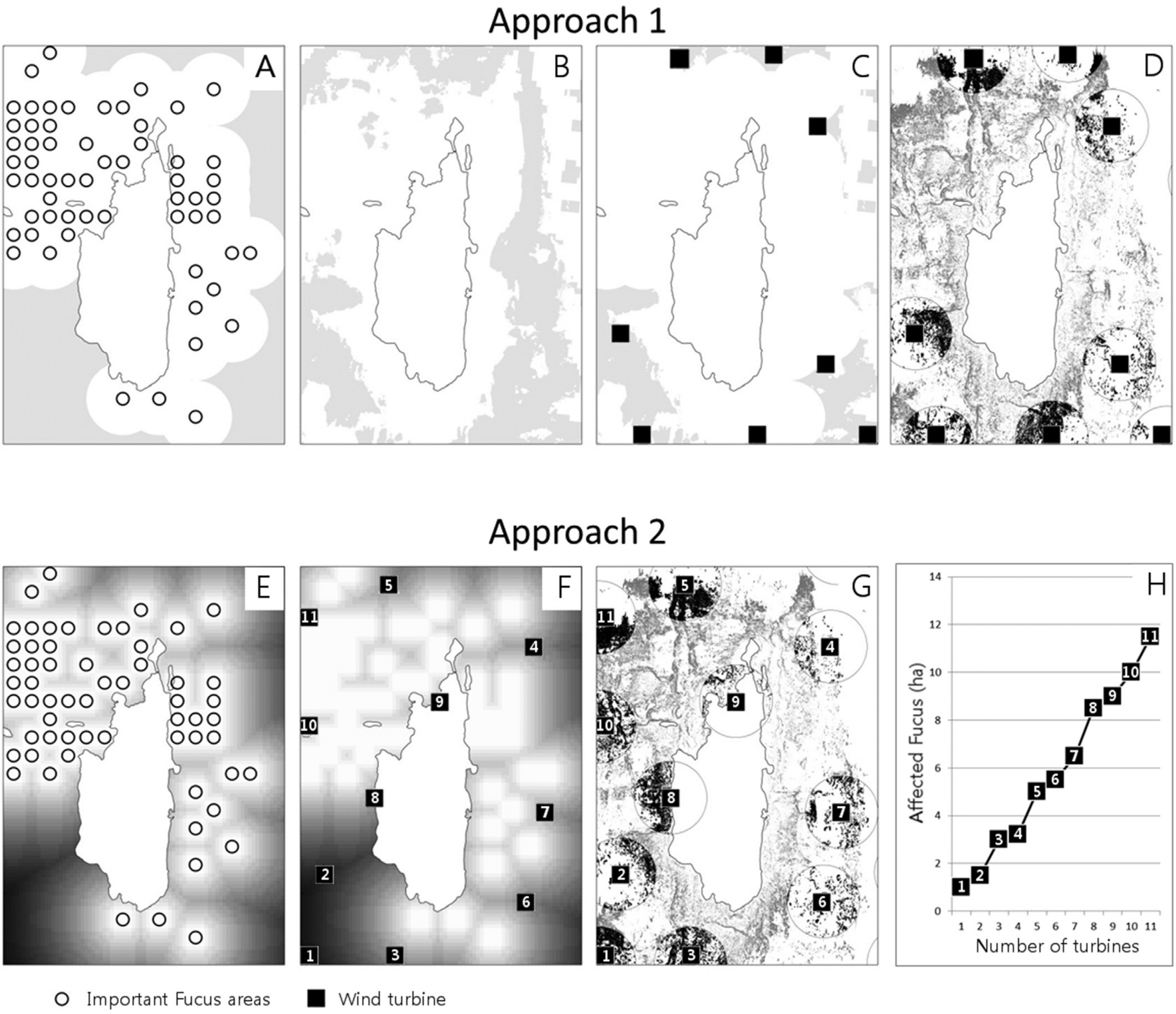

Fig. 3. Visualization of selected work phases in the placement of the hypothetical wind turbines. A) Restricting planning with buffers around important *Fucus* areas. B) Restricting planning to chosen depth range. C) Placing turbines to available areas. D) Calculating coverage of affected *Fucus* around the turbines. E) Calculating distance from important *Fucus* areas. F) Placing the turbines one by one starting with the location furthest from important *Fucus* areas. G) Calculating affected *Fucus* coverage for each turbine individually. H) Calculating the cumulative effect for each added turbine.

maximum number of potentially suitable wind turbine sites in four different depth ranges (0–5 m, 5–10 m, 10–15 m and 15–20 m) with minor disturbance to the important *Fucus* habitats. Turbines were placed one by one using the shallowest available site as the starting point and with the rule of having a minimum distance of 500 m to any already defined turbine location and a minimum of 200 m to the nearest important *Fucus* areas (not relevant in the conventional planning scheme). In Approach 2, wind turbine sites were defined one by one as far from the important *Fucus* areas as possible, until all locations in the research area were used. As the conventional planning scheme lacked information about the distribution of *Fucus*, consecutive wind turbine sites were defined at random order into grid cells of 500 × 500 m.

3. Results

The conventional planning scheme allows the placement of the highest number of wind turbines in each depth class (Fig. 4). However, this scheme also results in considerable overlap with the *Fucus* areas, in terms of both the total affected area and the mean area per turbine. The numbers of possible turbine locations as well as the overlapping areas with the *Fucus* areas are somewhat lower in the inventory-assisted planning scheme. Although the number of available sites was substantially fewer with LIDAR data, most of the overlap with *Fucus* areas could be avoided even though scattered *Fucus* patches were not used to restrict the planning.

Different planning schemes also yielded dissimilar outcomes when the turbine placement process tried to avoid overlap with the *Fucus* areas (Fig. 5). In the conventional planning scheme the overlap with the *Fucus* areas increased almost linearly with the increasing number of planned turbines. Although the degree of overlap with *Fucus* areas in the inventory-assisted planning scheme was smaller, in this case almost every new turbine introduced new overlap. By contrast, in the LIDAR-assisted planning scheme the

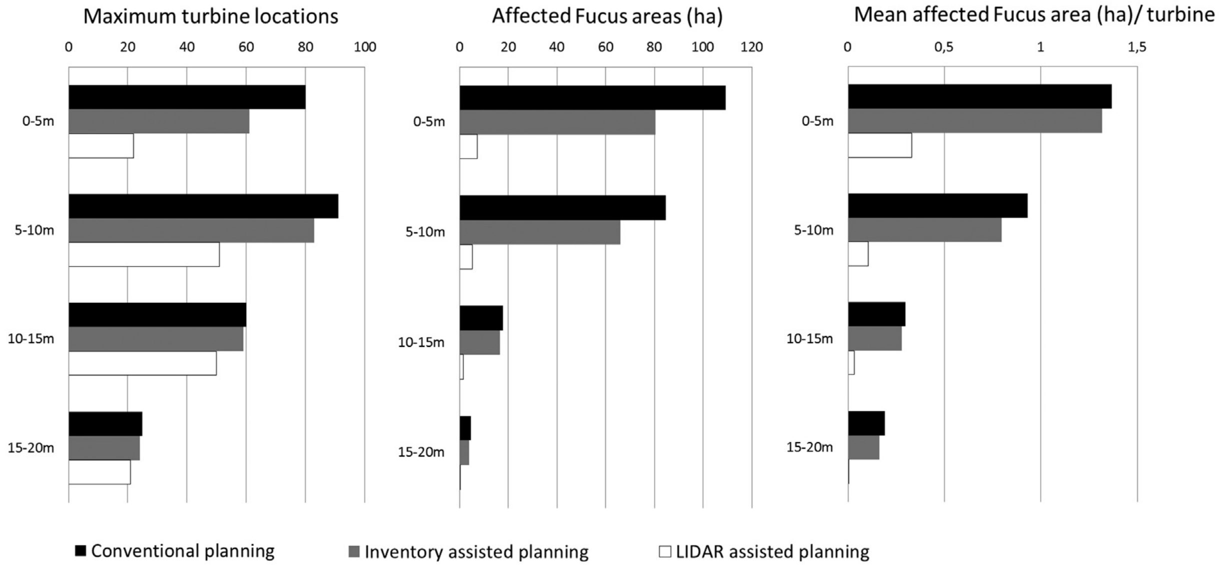

Fig. 4. Results from planning a maximum number of turbine locations in four different depth classes according to the compared planning schemes.

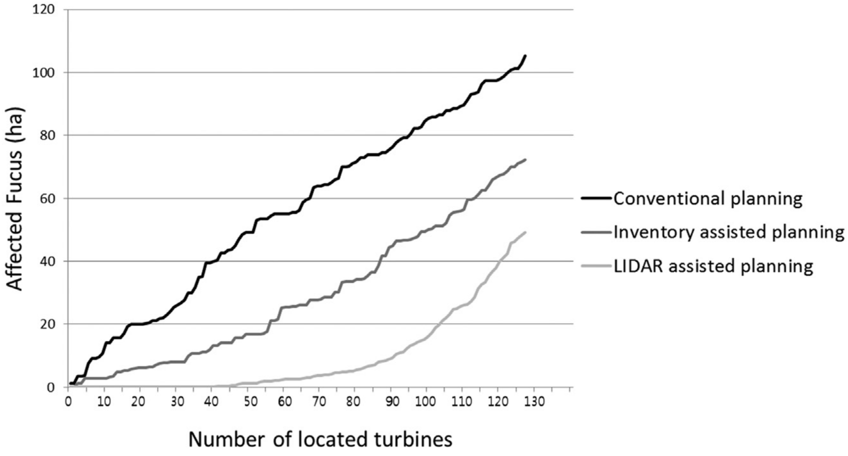

Fig. 5. Placement of an accumulating number of consecutive wind turbines to the study area according to the three compared planning schemes. Vertical axis shows the area within 200 m from the turbines overlapping with *Fucus* areas.

total overlap with the *Fucus* areas remained at a very low level until some fifty possible turbine sites were found and rapid overlap did not occur until after approximately one hundred possible turbine locations were defined.

4. Discussion

Current energy policies in Europe reinforce wind energy production in coastal and offshore locations (Henderson et al., 2003). The site selection process has to consider a number of criteria, from the local wind resources (Hasager et al., 2011) to the implementation of responsible coastal and marine planning (Douvere, 2008; Haggett, 2008). The definition of optimal sites for wind turbines consequently requires a multi-criteria approach that can be supported by advanced mathematics, fuzzy set theory and spatial modeling (El-Shimy, 2010; Fetanat and Khorasaninejad, 2015). The success of any such effort finally depends on the quality of the input data, such as maps showing the distributions of disturbance-sensitive habitats. Deficient data may delay, hinder or even stop important development projects. Alternatively, if projects were to be accepted instead on the basis of inadequate data, unexpected impacts may occur, such as habitat loss, biodiversity decline, degradation of primary production or reduction in fish stocks. An increase in available data, as well as an understanding of the most suitable datasets for different kinds of developments projects would undoubtedly contribute to Environmental Impact Assessments and Marine Spatial Planning processes, making them more reliable and efficient.

The potential impacts of wind turbines for coastal ecology range from bird collision risk to underwater habitat loss, noise, vibration and electromagnetic fields (Garthe and Hüppop, 2004; Gill, 2005; Inger et al., 2009). In reviewing the influences of turbine underwater noise on marine mammals, Madsen et al. (2006) highlighted the scarcity of appropriate data on the behavioral reactions of the exposed animals. Since data on the distributions of sensitive marine biotopes also tends to be scarce, tension may grow between wind power developers and environmental authorities. According to the precautionary principle, any potentially adverse effects should not be dismissed. However, the need to collect extensive field data for reliable assessments may result in high costs and delays. This is where efficient and reliable benthic habitat mapping methods are needed. Our results reveal how the use of different input data can result in highly dissimilar planning outcomes. The conventional planning scheme allowed us to determine the highest number of potential wind turbine sites but resulted in the most severe overlap with the *Fucus* areas. The inventory-assisted planning scheme reduced both the number of potential wind turbine sites and their expected environmental impact. However, considering the exceptionally dense network of field truth data in this area the environmental benefits were rather small. It is likely that while the usability of field inventory data could be improved by modeling, at the moment the resolutions of the required environmental variables are too coarse for detailed studies. The use of airborne LIDAR made it possible to define a good number of wind turbine sites with a significantly reduced environmental impact.

Our study supports LIDAR-based benthic habitat mapping as a potentially useful method for coastal and marine planning with some reservations. First, sufficient field inventories need to be done to calibrate and validate the classification based on remotely sensed data. Second, the distinguishability of the sensitive habitat type(s) under focus, as well as the spatial resolution of their remote sensing based mapping should be adequately high. This condition may not be met if there are more than one key habitat types to consider, the targeted submerged habitat types do not differentiate from their surrounding areas or the key habitat occurs in depths that cannot be reliably mapped with LIDAR. The latter is critical also with regard to the timing of the LIDAR campaign, since in the Baltic Sea at least, seawater optics are variable in both seasonal and spatial terms (Luhtala et al., 2013). Third, the size of the target area and the goals of the respective planning endeavor contribute to the cost-benefit assessment. When the target area extend over large areas, a LIDAR campaign can be economical. By contrast, when the need is to assess the suitability of some pre-determined wind turbine locations only, then the best choice could be to conduct conventional field inventories at the site.

5. Conclusions

The risk of damaging important benthic habitats by inappropriate planning can be reduced by distribution mapping of these submerged habitats. Point inventory data can be insufficient since the maps used in planning must be spatially explicit. The application of airborne LIDAR can be proficient when the benthic habitats of interest are identifiable with sufficient accuracy. The best results are likely achieved through a combination of field inventories documenting ground truth and the use of LIDAR to achieve spatially consistent mapping. Defining potential sites for shallow water wind turbines was shown to result in highly dissimilar outcomes by the use different input data.

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