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Influence of artefacts in marine digital terrain models on habitat maps and species distribution models: a multiscale assessment

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Abstract

Remote sensing techniques are currently the main methods providing elevation data used to produce Digital Terrain Models (DTM). Terrain attributes (*e.g.* slope, orientation, rugosity) derived from DTMs are commonly used as surrogates of species or habitat distribution in ecological studies. While DTMs' errors are known to propagate to terrain attributes, their impact on ecological analyses is however rarely documented. This study assessed the impact of data acquisition artefacts on habitat maps and species distribution models. DTMs of German Bank (off Nova Scotia, Canada) at five different spatial scales were altered to artificially introduce different levels of common data acquisition artefacts. These data were used in 615 unsupervised classifications to map potential habitat types based on biophysical characteristics of the area, and in 615 supervised classifications (MaxEnt) to predict sea scallop distribution across the area. Differences between maps and models built from altered data and reference maps and models were assessed. Roll artefacts decreased map accuracy (up to 14% lower) and artificially increased models' performances. Impacts from other types of artefacts were not consistent, either decreasing or increasing accuracy and performance measures. The spatial distribution of habitats and spatial predictions of sea scallop distributions were always affected by data quality (*i.e.* artefacts), spatial scale of the data, and the selection of variables used in the classifications. This research demonstrates the importance of these three factors in building a study design, and highlights the need for error quantification protocols that can assist when maps and models are used in decision-making, for instance in conservation and management.

Introduction

In the last decades, remote sensing has become the main method used for collecting elevation data used in the production of Digital Terrain Models (DTM). All DTMs carry a certain level of error (Gessler et al. 2009) caused by random noise, systematic errors and artefacts (Wise 2000). Artefacts were characterized by Reuter et al. (2009)) as "distinct erratic features" that are made of improbable and incorrect values. Artefacts can be found in DTMs collected from any remote sensing systems (Fisher and Tate 2006; Sofia et al. 2013) and at all scales.

Artefacts can be introduced by the interpolation method used to create the DTM (Sofia et al. 2013), the motion and location of the acquisition platform (Harrison et al. 2009), timing or log frequency issue in the surveying system (Lecours and Devillers 2015) or a lack of or an inappropriate correction of ionospheric and atmospheric conditions (Li and Goldstein 1990). Artefacts can be problematic as they influence data quality more than other types of errors like noise and imprecise measurements (Rousseaux 2003) and can be very subtle in the DTM (Filin 2003), making them "the most significant errors in a spatial or statistical analysis because they are not easily detected yet introduce significant bias" (Brown and Bara 1994).

DTMs are now commonly used in Geographic Information Systems (GIS) to derive terrain attributes (*e.g.* slope, orientation, rugosity) that can be used as surrogates for other phenomena in fields like ecology (Bolstad et al. 1998) and biogeography (Franklin 2013). Artefacts in DTMs were shown to sometimes propagate to the derived terrain attributes (Sofia et al. 2013; Lecours et al. 2017a) and are likely to impact subsequent analyses (Arbia et al. 1998; Heuvelink 1998). Mapping and quantifying error propagation throughout analysis have received some attention in the geospatial literature (*e.g.* Fisher and Tate 2006; Wilson 2012) but are rarely performed by DTM users from other disciplines (van Niel and Austin 2007). Quantifying error propagation from DTM is especially relevant for the production of species distribution models (SDM) and habitat maps (van Niel et al. 2004; Peters et al. 2009) that often combine terrain attributes with other environmental data (Franklin 1995; Guisan and Zimmermann 2000; Williams et al. 2012; Leempoel et al. 2015). These maps and models are regularly used to support decision-making in conservation (Miller 2010; Guisan et al. 2013). However, a lack of understanding of errors, their propagation and spatial distribution in maps may result in inaccurate maps and models that could lead to inappropriate decisions (Beale and Lennon 2012), and negative impacts on biodiversity or stakeholders (Beven 2000; Regan et al. 2005; Etnoyer and Morgan 2007). However, issues related to spatial data error are often overlooked (but see van Niel et al. 2004 and Livne and Svoray 2011). To our knowledge, the influence of data acquisition artefact errors in DTMs has never been assessed on maps resulting from SDM or habitat mapping exercises.

The objective of this study was to describe the impact of some common remotely sensed data acquisition artefacts on marine habitat maps and SDMs. Our specific objectives were to (1) quantify the impact of artefacts on habitat maps accuracy and SDMs performance, to (2) assess if impacts are dependent on spatial scale, and to (3) assess if impacts can be attenuated when combining the affected data with other environmental data of better quality. Our hypotheses were that artefacts do negatively affect habitat maps and SDMs, that the impacts are greater at finer scales, and that the addition of relatively better quality data reduces the impacts of artefacts on maps and models.

Materials and Methods

Case study and data

This article explored the impact of DTM artefacts on habitat maps using a case study from the marine environment. The marine realm provides an ideal case as it has been suggested that underwater DTMs, or Digital Bathymetric Models (DBM), may be more prone to errors and artefacts than terrestrial DTMs (Hughes-Clarke et al. 1996; Passalacqua et al. 2015; Lecours et al. 2016a). DBMs are often the only available datasets used to characterize deep-water environments due to difficulties to observe and sample other environmental characteristics (Solan et al. 2003; Robinson et al. 2011). If multibeam echosounders (MBES) are currently the best technology enabling the collection of large DBMs (Kenny et al. 2003), most bathymetric surfaces generated from these systems still contain some artefacts (Hughes-Clarke 2003a; Roman and Singh 2006). Since these artefacts are often within hydrographic error standards (Hughes-Clarke 2003a) and appear even when appropriate calibration and corrections are made (Erikstad et al. 2013), they are often considered inherent to the data and tend to be overlooked by DBM end-users.

This article used bathymetric data for German Bank, off Nova Scotia (Canada), in the eastern Gulf of Maine (Fig. 1). The surveyed area covers 3650 km^2 of the Scotian Shelf and has been extensively studied in previous works (*e.g.* DFO, 2006; Brown et al. 2012; Todd et al. 2012; Smith et al. 2017). Bathymetric data were collected by the Canadian Hydrographic Service (CHS) and were corrected in post-processing for tide, motion, and sound velocity. The corrected soundings were used to generate reference DBMs at five different spatial resolutions: 10 m, 25 m, 50 m, 75 m and 100 m in the bathymetric processing software CARIS HIPS and SIPS v.9.0. These five reference DBMs were assumed to be free of artefacts, and following methods described in Lecours et al. (2017a), 10 different amplitudes of heave, pitch, roll and time artefacts were artificially introduced in them by altering the calibration measures of the different surveys (Table 1). The ten levels of amplitude for each type of artefacts were derived from the standard deviation (σ; Table 1) of the ship's recorded range of motion at the time of surveys. As described in Lecours et al. (2017a), these common artefacts were selected based on their different theoretical

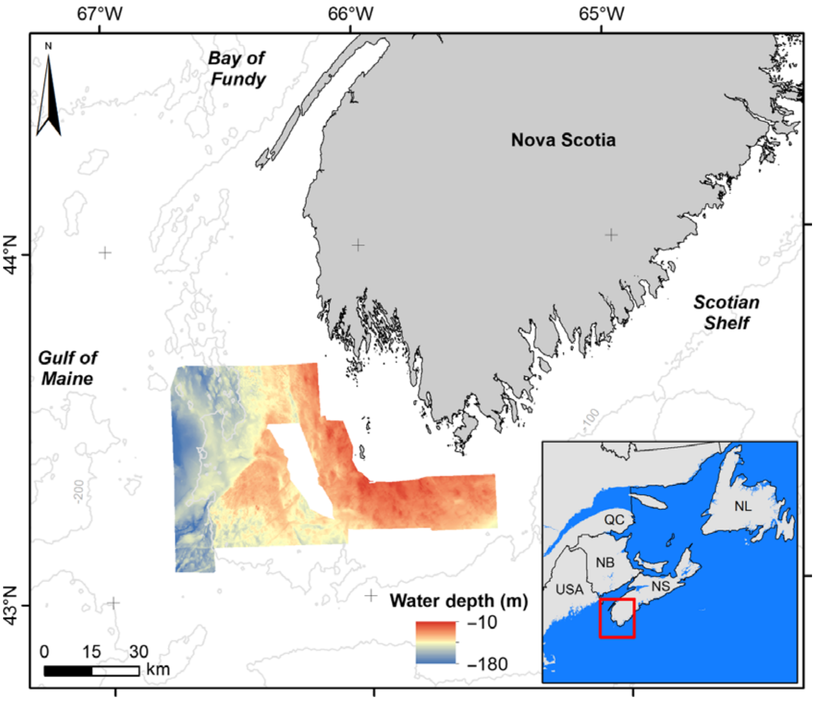

Figure 1. Digital bathymetric model of the German Bank study area.

Table 1. Levels of artefacts introduced in the five reference DBMs. Standard deviations (σ) were derived from the recorded motion at time of survey.

	Level of induced artefact				
	σ	2σ	3σ	4σ	5σ
Heave (m)	±0.33	±0.66	±0.99	±1.32	±1.65
Pitch (°)	±1.65	±3.30	±4.95	±6.60	±8.25
Roll (°)	±1.01	±2.02	±3.03	±4.04	±5.05
Time (sec)	±0.25	±0.50	±0.75	±1.00	±1.25

A positive pitch indicates that the bow is up and a positive roll means that the port side is up.

impact on data; pitch impacts bathymetric data in both horizontal and vertical planes, heave impacts them in a vertical plane, roll affects soundings that are further away from the nadir in a vertical plane – consequently affecting areas that overlap between different survey lines – and time causes a relative shift of adjacent lines in the horizontal plane (see Hughes-Clarke 1997, 2002, 2003a,b; Lurton 2010). Similar artefacts can also be found in other types of remote sensing like LiDAR (Brown and Bara 1994; Filin 2003; Lichti and Skaloud 2010). The artefacts were systematically introduced to provide controlled conditions that enable comparisons of results, as often performed in evaluations of the impact of error on analyses (Reuter et al. 2009).

Six terrain attributes that together summarize topographic variability were derived from the reference and altered DBMs using the TASSE toolbox for ArcGIS (Lecours 2015): slope, easterness and northerness, topographic mean, rugosity and topographic position (see Lecours et al. 2016b, 2017b). Backscatter data (*i.e.* acoustic reflectance) were simultaneously recorded with the bathymetric data. The backscatter data were processed and transformed by Brown et al. (2012) into three derivative layers that inform on seafloor properties (*e.g.* surficial geology, porosity): Q1, Q2 and Q3. Finally, two sets of ground-truth data from Brown et al. (2012) were used: (1) 3190 geo-referenced photographs of the seafloor classified into five habitat types (reef, glacial till, silt and mud, silt with sediment bed forms, sand with sediment bed forms and highly abundant sand dollars (*Echinarachnius parma*)), and (2) 4816 geo-referenced sea scallop observations (*Placopecten magellanicus*). Details on how these data were collected and processed and examples of photographs of the seafloor can be found in DFO (2006) and Brown et al. (2012).

Habitat Maps and SDMs

Using the 205 sets of bathymetric and terrain attribute surfaces (*i.e.* one set for each of the 10 levels of artefacts, for the four types of artefacts, at five different resolutions, in addition to a reference set for each of the five resolutions), habitat maps and SDMs were produced for three scenarios. First, maps and models were generated using only the bathymetry and the six terrain attribute surfaces, thus accounting only for terrain morphology (*i.e.* hereafter referred to as "7 layers" scenario). Then, maps and models were produced using all the available data (bathymetry, slope, easterness, northerness, topographic mean, rugosity, topographic position, Q1, Q2 and Q3) (*i.e.* "10 layers" scenario). The addition of backscatter data in this scenario was done to address our third hypothesis regarding the addition of relatively better quality data to the mapping process. Finally, maps and models were built using only non-correlated variables (*i.e.* "8 layers" scenario). On German Bank, the steepest areas are also the ones with the highest rugosity, resulting in a high correlation between the slope and rugosity data layers. Also, bathymetry is highly correlated with topographic mean as they are closely related (see Lecours et al. 2017b). Rugosity and topographic mean were therefore not used for the last sets of maps and models. The data for the eight layers scenario were thus bathymetry, slope, easterness, northerness, topographic position, Q1, Q2 and Q3. Overall, 615 habitat maps and 615 SDMs were produced and analysed by using the 205 sets of data for each of the three scenarios with both approaches.

The method used to generate habitat maps is based on the concept of benthoscape (Zajac 2008), a representation of the biophysical characteristics of an area generated by adopting a landscape style approach similar to when maps of landscape features are generated from terrestrial datasets. Such approach was used by Brown et al. (2012) to map features on the seafloor that could be resolved within the acoustic remotely sensed data, thus not attempting to delineate seafloor attributes beyond what the remote sensing techniques were capable of resolving. This approach segments the different data layers into a statistically optimum number of classes that are then spatially compared to the geo-referenced photographs and recombined based on best match with the different habitat types (see Brown et al. 2012). The Modified k-Means unsupervised classification tool of Whitebox GAT v.3.2 was used to produce these maps, and confusion matrices were built to calculate the kappa coefficient of agreement of each map (Boyce et al. 2002).

SDMs were generated based on maximum entropy (MaxEnt), a common and effective method (Phillips et al. 2006; Monk et al. 2010), that used the sea scallop observations to segment the environmental data and quantify sea scallop habitat suitability across the area. SDMs were computed using the MaxEnt software v.3.3.3k with the same settings as in Brown et al. (2012). Area under the curve (AUC) derived from threshold independent receiver operating curves were also measured to quantify the performance of the models and enable comparisons (Phillips et al. 2006): AUC_{Train} was measured to evaluate the goodness-of-fit of models to the training data, and AUC_{Test} was used to evaluate the ability of models to perform well on an independent dataset (*i.e.* validation samples) (Fitzpatrick et al. 2013). These two measures were combined to compare models' performance, robustness and generalizability (Vaughan and Ormerod 2005; Warren and Seifert 2011). AUC_{Diff}–the difference between AUC_{Train} and AUC_{Test}–was used to quantify generalizability (*i.e.* transportability, transferability): a high value is an indication that a model over-fitted the training data and does not replicate well to a different dataset. Details on these measures can be found in Lecours et al. (2016b). Finally, correlations between model outputs were calculated to evaluate spatial similarity of predictions.

Results

Habitat maps

The average kappa coefficients of agreement of all maps produced with altered data and their standard deviation are presented in the supporting information (Table S1), while the individual kappa of the 615 habitat maps are presented in Figure 2. In general, habitat maps produced using 10 layers provided the best classifications, followed by those using eight layers and those built from only seven layers. However, map accuracy varied less for the scenario with eight layers (*i.e.* it was more consistent). Heave was generally the artefact type that made map accuracy vary the least, while roll artefacts usually made map accuracy vary the most. In average (Table S1), only three sets of maps showed a scale-dependent pattern for which maps produced from finer-scale data were more impacted by artefacts than maps made from broader-scale data. These sets all belong to the scenario with 10 layers and were maps impacted by pitch, roll and time. A visual assessment of the results showed that the presence of artefacts in data used to produce habitat maps has a noticeable influence on the spatial distribution of the habitats (*cf.* Fig. 3). When matching the total area misclassified because of artefacts–that is, when comparing the classifications made from altered data to one made from reference data–to the difference in kappa coefficient between these maps, results show that a little difference in kappa coefficient can translate into large differences in spatial output (*cf.* Fig. 3C).

Except for maps affected by roll artefacts, the reference maps did not always produce the best outcome in terms of accuracy: while all habitat maps impacted by any level of roll artefact performed worse than the reference maps, an important number of maps made from altered data had a higher kappa coefficient than their corresponding reference maps. This was observed regardless of scale and scenario. Overall, 47% of the habitat maps altered by pitch had a higher kappa coefficient than their

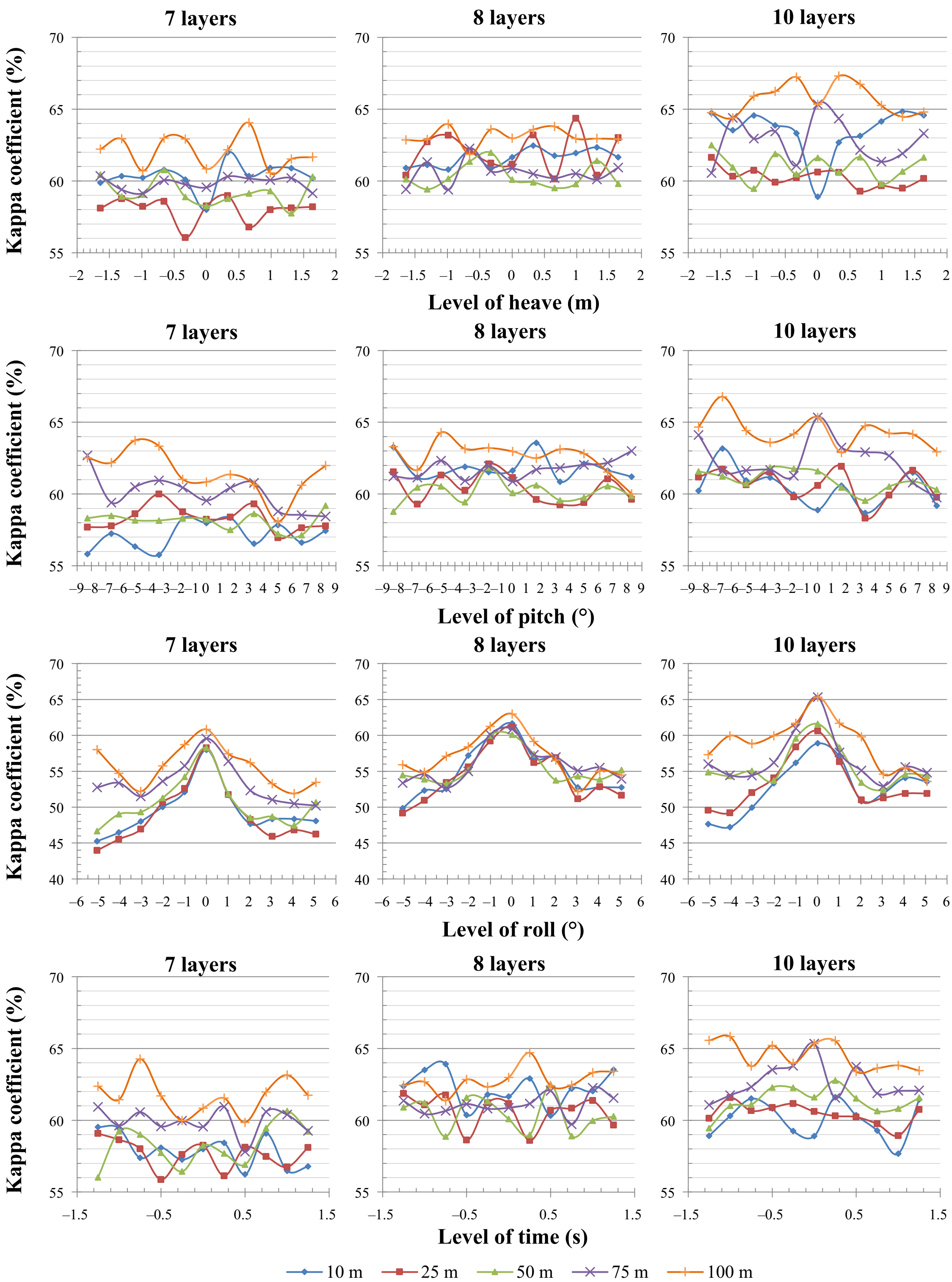

Figure 2. Kappa coefficients of agreement of the 615 habitat maps.

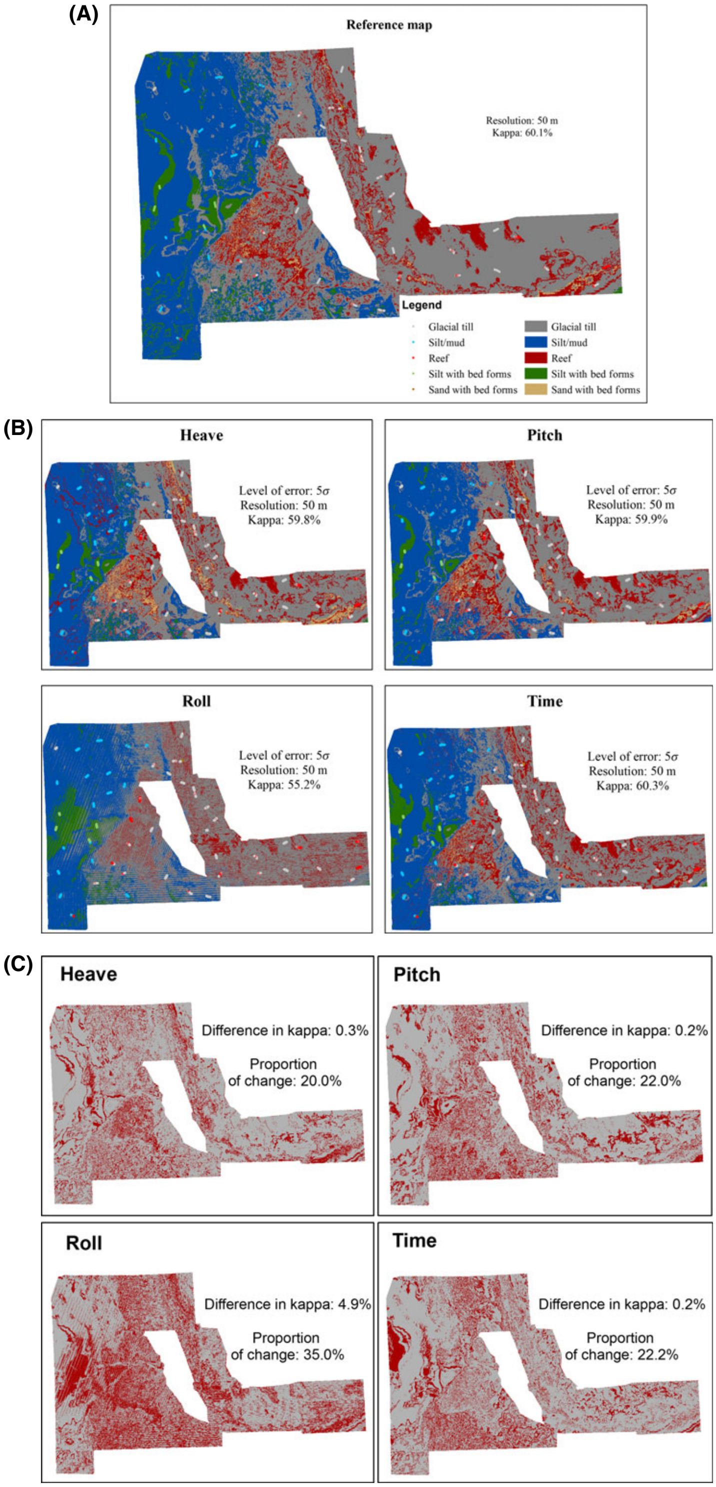

Figure 3. Examples of habitat maps produced with eight layers at 50 m resolution, overlaid by the ground-truth data. The colour of the ground-truth data matches the classification's colour when appropriately classified. (A) shows the reference map that was built with data that were assumed free of artefacts. (B) shows maps built from data that were impacted by different types of artefacts. (C) shows the spatial distribution of the change in habitat map classification between the maps from (B) and the map from (A). Red pixels indicate change while grey pixels are those that were classified as the same habitat type in the two compared classifications.

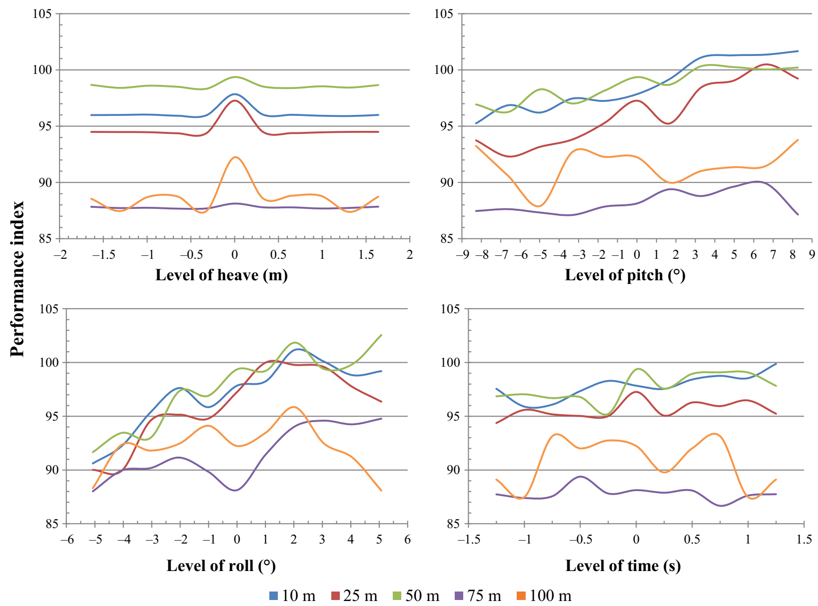

Figure 4. Change in performance index (ratio of AUC_{Test} on standard deviation) as the level of artefacts in the data changes, for the models built from eight layers. Models that perform better have a high AUC_{Test} and models that are more robust have a low standard deviation. High-performance models are often less robust than less performing models: the performance index thus captures the trade-off between performance and robustness, with higher values of performance index indicating a better trade-off.

corresponding reference map, and that percentage was higher for time (50%) and heave (55%). No particular scale-dependent patterns were observed, except for habitat maps made from seven layers and impacted by pitch, for which a greater amount of maps performed better than the reference maps at broader scales.

Species distribution models

Figure 4 shows how the SDMs' performance and robustness change as artefacts are introduced in the input DBMs for the eight layers scenario. For all types of artefacts, no pattern could be observed regarding whether some scales were more impacted than others, or whether a greater level of artefact resulted in higher or lower performance or robustness.

In general, results show that introducing heave artefacts decreased models' performance and tend to also decrease models' robustness. One major exception was observed to these patterns: at 75 m resolution, 7 and 10 layers models performed better than the reference models. The two reference models in these cases had a higher standard deviation and a lower AUC_{Test}. Overall, about 87% of models impacted by heave had a lower performance index than their comparable reference model. About 39% of models with pitch artefacts had a higher AUC_{Test} than their respective reference model while 36% of them were more robust, which resulted in 41% of these models with a higher performance index than their reference model (Fig. 4). Roll artefacts boosted model performance, as 87% of models built from altered data had higher AUC_{Test} measures than the reference models. However, only 26% of the models impacted by roll artefacts were more robust than the reference models. The combination of these two metrics into the performance index indicated that 56% of models impacted by artefacts had a higher index than the reference models. In terms of time artefacts, 29% of the models that were built from altered data performed better than the reference models and 11% were more robust, resulting in 26% of them having a higher performance index than reference models.

In terms of generalizability, it was difficult to find any consistent general patterns except for those models affected by roll: 95% of them showed a greater generalizability index than the reference models. On the other end, the presence of heave artefacts decreased the generalizability in 80% of the cases, compared to 53% of models affected by pitch and 66% of those affected by time (Fig. 5).

Regarding spatial outputs, the presence of artefacts always introduced discrepancies in the distribution of relative habitat suitability (*cf.* Figs. 6 and S1). While the average discrepancies could be globally small (*e.g.* 2.2%), they could be locally important (*e.g.* 58.9%). It is also interesting to note that a high measure of correlation between a model impacted by artefacts and its reference

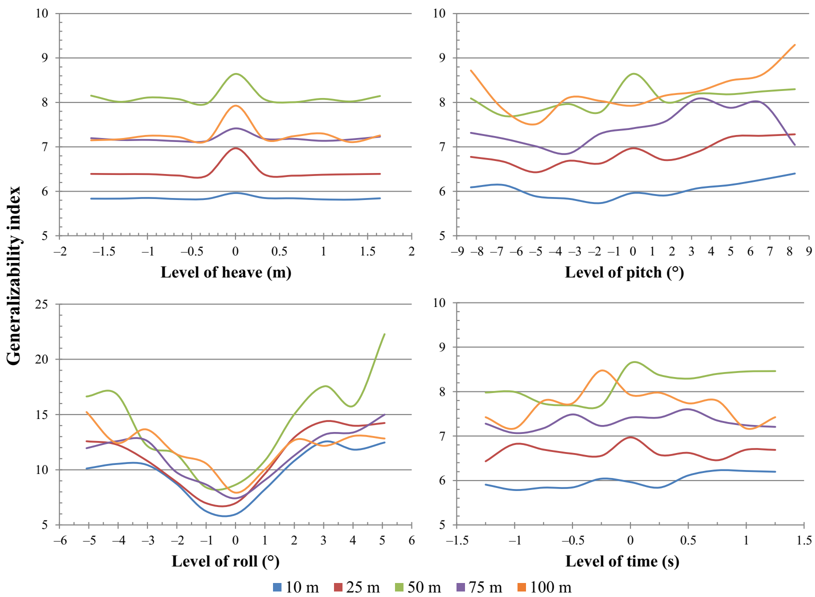

Figure 5. Change in generalizability index (ratio of AUC_{Train} on AUC_{Diff}) as the level of artefacts in the data changes, for the models built from eight layers. Higher values indicate more generalizable or replicable models.

model did not necessarily involve high similarity between those. For instance, a correlation coefficient of 0.963 still resulted in 23% of the area for which differences in relative habitat suitability were >5% (Fig. 6).

In general, models accounting only for topography and depth (seven layers) were consistently the most affected by artefacts in comparison to the reference models (Fig. S1), while those built with uncorrelated variables (eight layers) were often the least impacted. The ranges in correlation coefficients (Fig. S1) were usually not very big for heave artefacts and were in average lower for roll artefacts. Overall, roll seemed to have the most impact on the spatial distribution of relative habitat suitability of sea scallop. No clear pattern was observed in terms of scale, although roll artefacts seemed to produce models that were more similar to the reference ones at coarser scales, and the extreme scales (10 and 100 m) seemed to be a bit more impacted by heave, time and pitch than the intermediate scales (25–75 m).

Discussion

Impacts of artefacts on habitat maps and SDMs

Our first hypothesis was that artefacts in bathymetry that propagate to terrain attributes would impact habitat maps and SDMs in a negative way. Results show that this is not always the case. While we were expecting map accuracy to decrease as a function of level of artefacts, only maps impacted by roll demonstrated such relationship. Results show that the other types of artefacts sometimes artificially increased map accuracy, although not in a predictable way. A higher level of artefact did not necessarily result in a better or worse map or model than a lower level of artefact. About half of the habitat maps produced with data altered by heave, pitch and time artefacts performed better than the reference maps. While these results suggest a random pattern, they may also have been influenced by the approach used to quantify map accuracy. Since the habitats are represented on maps as clusters of pixels showing similar characteristics, they share some characteristics with areal data. Artefacts might thus influence the boundaries of these “zones” more than the area inside them. Because the ground-truth data are points that are more likely to fall within the middle of a zone than at its boundary, the kappa coefficients of agreement may not capture the change in boundary. A spatial assessment of the differences between the different habitat maps, as performed for instance in Figure 3C and in Diesing et al. (2014), could help better capture the influence of artefacts on the delineation of the different habitat zones. Considering the amount of maps produced in this study, this would be computationally intensive but such an approach should be considered in future work. These results however yield an important conclusion regarding the methods commonly

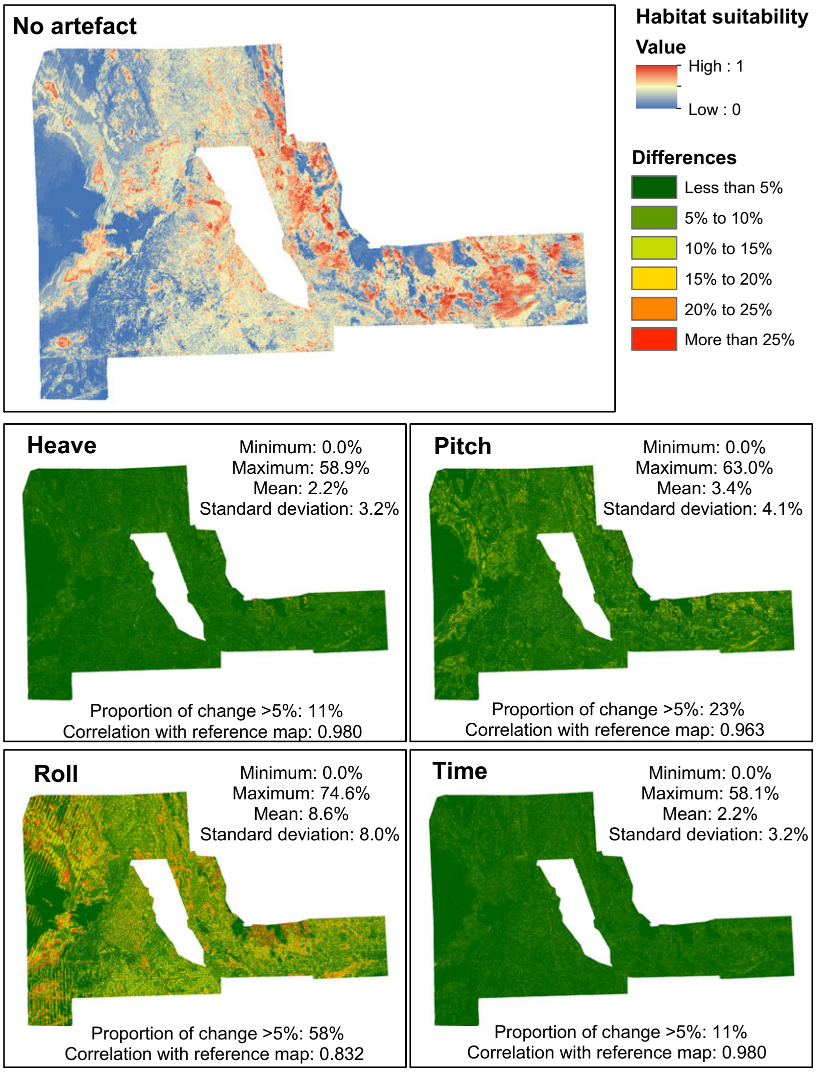

Figure 6. Differences in distribution of relative habitat suitability of sea scallops between models affected by artefacts and a reference model (top). The scenario represented is the one with eight layers at 50 m resolution. The level of error represented is the highest one (5σ, Table 1).

used in the literature to quantify classification and habitat map accuracy: measures using point data to validate classifications of zones may be biased by not capturing the variability of the classifications along zone boundaries.

The analysis of SDMs yielded similar conclusions to the analysis of habitat maps but from different types of artefacts. Heave artefacts had generally a negative impact on the performance of models, with some exceptions (*e.g.* 75 m resolution models–which may indicate that this particular scale does not capture the relevant drivers of species distribution). Some models impacted by pitch and time performed better than the reference models. Models impacted by roll artefacts clearly contradicted our hypothesis: the performance of most of these models was artificially increased by the presence of roll artefacts. This could be explained by the fact that sea scallops distribution is driven by rugosity (Brown et al. 2012), and artefacts like roll and pitch artificially increase the rugosity of an area. Models produced with data impacted by these artefacts would thus artificially increase the relative habitat suitability of sea scallops across the entire area, resulting in a higher prediction success when validated against the test data. The increase in high values of relative habitat suitability was confirmed by visual comparison (*cf.* Fig. 6) but also by the high differences in spatial correlation recorded for pitch and particularly for roll (*cf.* Fig. S1).

Our second hypothesis stated that the impacts of artefacts in bathymetry and terrain attributes should be greater at finer scales. This hypothesis was based on the fact that the propagation of artefacts from DTM to terrain attributes was previously found to be scale-dependent (*cf.* Lecours et al. 2017a). Results from both unsupervised and supervised classifications did not confirm, neither did they refute, this hypothesis as no particular scale-dependent patterns could be identified. The difference between the scale-dependent propagation of DTM artefacts in terrain attributes and the scale-independent propagation of these artefacts in habitat maps and SDMs may be explained by the integration of a biological/ecological context. The presence of artefacts in finer-scale data may not result in a poor habitat classification if these data and the scales at which they were collected and analysed do not have an ecological meaning or do not match the ecological scale of the phenomenon being studied, thus being unsuitable regardless of their quality.

Finally, our third hypothesis was that the addition of relatively better quality data would reduce the impacts of artefacts on maps and models. Results suggest that this hypothesis is true for the habitat maps, as maps built with the relatively good quality backscatter data were generally more accurate. It however remains unclear whether this improvement was caused by the quality of the data or their nature (*i.e.* backscatter), which in this particular case was known to be ecologically relevant (Brown et al. 2012). The latter option is the most likely, considering results from Lecours et al. (2016b) that showed that maps and models of the same area produced only with backscatter and depth data performed very well. Further work is thus required to validate or invalidate this hypothesis with more certainty. In addition, results showed that the range in measures of accuracy was more stable when uncorrelated data were used, which could be an indication that a better choice in input variable has the potential to stabilize and attenuate the impacts of artefacts.

Spatial errors in ecology: comparisons with other studies

In terms of data quality, the ecological literature has been oriented mostly towards measurement uncertainty, and the work performed on errors has largely focused on the positional accuracy of species observations (*e.g.* Moudrý and Šímová 2012). The impact of DTM artefacts has been studied before in a geomorphology and geomorphometry context (*e.g.* Bonin and Rousseaux 2005) but rarely in ecology. Of note is the work by van Niel et al. (2004) and van Niel and Austin (2007) that studied the effect of error in DTM on terrain attributes and predictive vegetation modelling. Despite different approaches and types of error studied, these studies and the current one yielded similar conclusions regarding the fact that errors do propagate throughout analyses, and affect distribution models although not in an easily predictable way. In another ecological study that looked at uncertainty and error propagation, Livne and Svoray (2011) identified the need to focus on assessing the behaviour of ecological models to spatial errors at different spatial resolutions. While this was addressed in the current study, results did not indicate any scale-dependent pattern.

In the marine environment, researchers are aware of artefacts as they are often, although not always (*e.g.* Lucieer et al. 2012), acknowledged (*e.g.* Blondel and Gómez Sichi 2009). When acknowledged, their implications for the ecological analysis being performed are often not discussed (*e.g.* Kostylev et al. 2001). The presence of artefacts in MBES data sometimes prevents their use or the use of their derived terrain attributes in ecological applications (*e.g.* Clements et al. 2010). When such data are still used, artefacts have been linked to habitat misclassifications (*e.g.* Micallef et al. 2012; Costa and Battista 2013), to noise in results from unsupervised classifications (*e.g.* Galparsoro et al. 2015), and to difficulties associated with identification of seabed features (*e.g.*, Dolan and Lucieer 2014), among other consequences. As part of their seabed mapping guidelines, the Norwegian Hydrographic Service indicated that “seabed features shall not be camouflaged by artefacts and artefacts must not appear as seabed features” (NHS, 2013), and that artefacts in the processed bathymetry “shall be kept at an insignificant level not disturbing the seabed image” (NHS, 2013). However, no procedures are indicated to assist in making decisions regarding how to deal with artefacts when they cannot be removed. This overview of the literature reflects the lack of understanding of how artefacts impact ecological analyses and interpretations, and the lack of knowledge on how to respond to the presence of artefacts. The work by Zieger et al. (2009) is however noteworthy as they used terrain attributes and seafloor classification to identify artefacts in flat areas before correcting for the misclassifications caused by artefacts. Such methods may however be inefficient in more complex areas as the classifications may be unable to distinguish which bathymetric patterns are artefacts and which are actual natural features.

While this study has focused on artefacts in multibeam bathymetric data, backscatter data are also often impacted by artefacts (*e.g.* Collier and Brown 2005; Che Hasan et al. 2012). Like for bathymetric data, some of these artefacts can be removed in post-processing (*e.g.* De Falco et al. 2010; Lamarche et al. 2011) but a complete removal is not always achieved. Backscatter data with artefacts have been widely used (*e.g.* Rattray et al. 2009; Roberts et al. 2009) as they may still yield useful observations. Other times however, they are judged unusable for the mapping or modelling exercise (*e.g.* Holmes et al. 2008). It has been recognized that there is a broad misunderstanding of backscatter within the end user community

(Lurton and Lamarche 2015). In this study, backscatter data were used to evaluate the impact of adding relatively better quality data to poor quality data within the same analysis. As done with bathymetry in this study, future work should evaluate the impacts of artefacts in backscatter data on habitat maps and SDMs. It is to be expected that like for bathymetry and terrain attributes, artefacts in backscatter data will have a greater impact if sediment properties are ecologically relevant to the species, area or problem studied. For instance, Copeland et al. (2013) noted that artefacts in the backscatter data resulted in an apparent striping pattern in their habitat classifications.

Implications for ecological applications

The results of this study have critical implications for ecological studies that use DTMs and their derived terrain attributes in their applications, which is a common practice (Bouchet et al. 2015; Lecours et al. 2016a). The use of environmental variables such as terrain attributes has been shown to improve predictions accuracy in SDMs (Dobrowski et al. 2008). However, this study showed that when artefact errors are present in DTMs, there is a trade-off between the improved prediction that would be gained from including the DTM and its derived terrain attributes and the risk to produce inaccurate predictions. Results showed that such predictions are not necessarily revealed as lower or absence of predictions, but can be important inflation in predictions. For instance, artefacts may alter the quantification of species-environment relationships by artificially increasing the importance of rugosity in habitat characterization. When rugosity is known to be a surrogate of a particular species distribution, this leads to an overestimation of the suitable habitat for that species.

Studies that include any assessment of data quality are rare (van Niel and Austin 2007). The current study highlighted the sensitivity of maps and models to the observational scale and spatial errors like artefacts. Many calls have been made in the literature for the quantification of uncertainty and error propagation throughout ecological analyses (*e.g.* Guisan et al. 2006; Lecours et al. 2015), and tools have been proposed to deal with uncertainty (*e.g.* the Data Uncertainty Engine by Brown and Heuvelink 2007) but not with errors. The ecological community that makes use of GIS tools and remote sensing techniques is usually aware of this need but such protocol are not yet implemented in any workflow. As stated by Li et al. (2012): “there are user communities who may be aware of spatial data quality issues but may not have at their disposal techniques and tools for data quality assurance.” Such tools, associated with proper standards, protocols and metadata, are becoming crucial to enable a proper incorporation of error modelling in the different applications workflow. This will eventually lead to results and interpretation that are grounded on solid foundations, and more informed decisions. While it is impossible to avoid error and uncertainty in ecological analyses, it is also important that practitioners stop avoiding it. An acknowledgement of errors like artefacts and a discussion on their potential impact on analyses will increase the chances to make more informed decisions when these data and analyses are used in contexts like conservation planning.

Conclusions

DTMs and terrain attributes are now commonly used in ecological studies. Despite an awareness of the presence of errors like artefacts in these data, their quality is rarely assessed, acknowledged or discussed. The goal of this study was to develop evidence linking the presence of artefacts in DTMs with the accuracy of analyses performed in ecological applications. Results demonstrated that artefacts do impact habitat maps and SDMs, although not in a predictable way. Roll artefacts showed the most predictable influence, decreasing the accuracy of habitat maps and artificially increasing the performance and generalizability of SDMs. Other types of artefacts sometimes increased map accuracy and model performance and generalizability or decreased them. These conclusions may however change if different data were used; perhaps that with higher-resolution data (e.g. 0.5–2 m), the relative magnitude of the artefacts would be more important and produce a much larger and consistent effect. Results showed that the importance of the impacts of artefacts on ecological applications strongly depend on whether or not the methods are grounded in ecological relevance, particularly in terms of the choice of variables and the spatial scale of the data. While the influence of errors on an analysis depends on the type and requirements of the analysis (Friedl et al., 2001), results gained in this study are transposable to other applications that use remotely sensed data like LiDAR-derived DTMs and encounter similar artefacts. This study also highlighted requirements for error quantification tools to become widely available to scientists and practitioners with a wide range of background and expertise. This will improve standards and protocols and lead to more quality-aware decisions in contexts like conservation.

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Data Accessibility

Data are available upon request from the Department of Fisheries and Oceans, Canada, for researchers who meet the criteria for access. Requests can be sent to chsinfo@dfo-mpo.gc.ca.

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Supporting Information

Additional supporting information may be found online in the supporting information tab for this article.

Table S1. Mean and standard deviation of kappa coefficients of agreement of the 10 maps made from altered data for each type of artefact, each scenario and each scale.

Figure S1. Spatial variation in predictions of sea scallops distribution as quantified by the range in correlation coefficients between models built from altered data and the reference models.

