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Underwater noise modelling for environmental impact assessment

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ABSTRACT

Assessment of underwater noise is increasingly required by regulators of development projects in marine and freshwater habitats, and noise pollution can be a constraining factor in the consenting process. Noise levels arising from the proposed activity are modelled and the potential impact on species of interest within the affected area is then evaluated. Although there is considerable uncertainty in the relationship between noise levels and impacts on aquatic species, the science underlying noise modelling is well understood. Nevertheless, many environmental impact assessments (EIAs) do not reflect best practice, and stakeholders and decision makers in the EIA process are often unfamiliar with the concepts and terminology that are integral to interpreting noise exposure predictions. In this paper, we review the process of underwater noise modelling and explore the factors affecting predictions of noise exposure. Finally, we illustrate the consequences of errors and uncertainties in noise modelling, and discuss future research needs to reduce uncertainty in noise assessments.

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1. Introduction

Underwater noise from human activities is known to have a number of adverse effects on aquatic life (Nowacek et al., 2007; Slabbekoorn et al., 2010; Williams et al., 2015). These can range from acute effects such as permanent or temporary hearing impairment (McCauley et al., 2003; Southall et al., 2007), to chronic effects such as developmental deficiencies (de Soto et al., 2013; Nedelec et al., 2014) and physiological stress (Wysocki et al., 2006; Wright et al., 2007; Rolland et al., 2012). While some anthropogenic noise is produced intentionally (e.g. naval sonar, echosounders), most noise sources are an incidental by-product of human activity (e.g. shipping, construction). Noise-generating activities are necessary for many proposed developments that are subject to a regulatory consenting process: construction may entail noise sources such as pile driving, dredging, or drilling, while geophysical surveys using seismic airguns are often needed prior to coastal construction and offshore energy developments. Many jurisdictions now require a noise impact assessment for proposed developments that have the potential to cause significant adverse impacts on key species. In some cases, effects on the wider ecosystem must also be considered.

The EIA process for underwater noise typically involves the application of quantitative noise exposure thresholds for particular species to a model of predicted noise levels at the site, resulting in effect zones — predicted areas for different categories of effect. Noise exposure thresholds are indicative noise levels at which certain effects (e.g. mortality, temporary hearing impairment, behavioural responses) are predicted, and may be defined for single noise exposures or for cumulative exposure to successive events. A number of different threshold criteria have been developed in recent years for marine mammals (e.g. Southall et al., 2007; NOAA, 2013, 2015) and fish (e.g. Popper et al., 2014), and it is expected that these will continue to evolve in light of new research into the effects of noise on aquatic species. Acknowledging that these thresholds form a necessary counterpart to modelling in noise impact assessments, the present work focuses on the acoustic modelling which underpins predictions of effect zones, independently of the (evolving) thresholds used to predict animal responses.

Modelling of underwater sound propagation has been an established discipline for decades, and has its origins in military applications of sonar technology. Several modelling approaches have been developed, each with differing suitability according to acoustic frequency range, water depth, computational requirements and ability to account for spatial variability in the environment (Jensen et al., 2011). The accuracy of model predictions depends both on employing an appropriate model and on the quality of the input data. Confidence in model predictions further requires validation with field measurements of sound propagation, and these measurements can also be used to optimise model parameters.

In practice, noise modelling for EIAs is often carried out using simplistic models, with limited environmental data, and without field measurements to ground-truth model predictions. In some cases, practitioners have developed proprietary models whose inner workings are not disclosed to regulators. This presents regulatory decision makers and their advisors with considerable uncertainty in the predictions of possible impacts (though this uncertainty may not be apparent). To better inform regulators, stakeholders, and developers of the factors which lead to uncertainty in noise assessments, this paper provides concrete

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examples of how different modelling procedures can affect predictions. By raising awareness of these issues, we aim to help promote best practice in noise impact assessments, and to enable more informed EIA processes for noise-generating developments.

2. Anatomy of a model

The basic objective of noise modelling for EIAs is to predict how much noise a particular activity will generate in the surrounding area. More formally, the aim is to model the received noise level (RL) at a given point (or points), based on the sound source level (SL) of the noise source, and the amount of sound energy which is lost as the sound wave propagates from the source to the receiver (propagation loss; PL). The relationship between these quantities is encapsulated in the classic sonar equation (Urick, 1983):

$$RL = \mathrm{SL} - PL \tag{1}$$

This straightforward expression is fundamental to the many approaches to modelling underwater noise, and its simplicity belies considerable complexity in the task of modelling the source level and propagation loss in order to predict received levels. In the following sections, we elaborate on the ways in which SL and PL can be predicted, and the various factors which affect the resulting estimates of RL.

3. Model selection

The first step in carrying out a noise assessment is to identify an appropriate sound propagation loss model. A large number of propagation models have been developed, based on several underlying mathematical methods, such as ray theory, normal modes, multipath expansion, wavenumber integration or parabolic equation (Porter, 1992; Collins, 1993; Porter and Liu, 1994; Etter, 2009, 2013; Jensen et al., 2011). No single model is applicable to all acoustic frequencies and environments (see Table 1). For a given scenario, a particular model may be limited by the validity of the model assumptions, by the number of computations required, or by instabilities in the model algorithm. Important factors to consider are the frequencies of sound to be modelled, the water depth, and whether spatial variation in the environment is significant (known as range dependence or range independence). Each of these factors should influence model selection. For example, models based on ray theory (e.g. BELLHOP; Porter and Liu, 1994) poorly describe the way that sound propagates at low frequencies in shallow water (Table 1), which is a common EIA modelling scenario.

For convenience, propagation loss is often estimated using simple spreading laws of the form.

$$PL = N\log_{10}(R) \tag{2}$$

where R is the distance from the noise source in metres, and N is a scaling factor. Since this simplistic approach does not account for complexities in the environment, it can only produce reasonable predictions for uncomplicated propagation scenarios, for example range-independent environments where extensive measurements from the study site are available to derive the value of N. Though widely used, spreading law models can lead to substantial errors if applied to the more complex environments typical of many coastal and inland waters.

To illustrate this, we compared predictions from a spreading law model to a parabolic equation model. For the spreading law model, sound levels were predicted using $15\log_{10}(R)$ (sometimes called 'intermediate spreading' or 'practical spreading'), which is derived from a theoretical treatment of sound propagation in shallow water obtained by Brekhovskikh (1965) and extended by Weston (1971). The parabolic equation model was based on RAM (developed by Collins, 1993, 1999), and utilised local data on bathymetry, sediment structure, and sound speed. Measurements of impact pile driving noise were made simultaneously at two locations in the Cromarty Firth, Scotland, and each model was then used to calculate the source level of piling (the sound level at a nominal distance of 1 m from the source). This source level was then used as the input to each model to predict levels of noise within the line-of-sight of the piling, yielding noise maps for each model (Figs. 1a and b).

Table 1
Applicability of the most common propagation models according to water depth, acoustic frequency, and range dependence (RI = range independent; RD = range dependent). Black cells indicate modelling approach is applicable and computationally efficient; grey cells indicate limitations in accuracy or computational efficiency; white cells indicate that the modelling approach is neither applicable nor practicable. Adapted from Etter (2009).

Model approach	Example algorithm	Applications							
		Shallow water				Deep water			
		Low frequency		High frequency		Low frequency		High frequency	
		RI	RD	RI	RD	RI	RD	RI	RD
Ray	BELLHOP (Porter and Liu, 1994)								
Normal mode	KRAKEN (Porter, 1992)								
Parabolic equation	RAM (Collins, 1993)								

Spreading laws assume that sound levels decrease monotonically with increasing distance from the source, and that the pattern of sound levels has circular symmetry, both of which are evident in Fig. 1a. In practice, however, sound propagation is much more complex. The RAM predictions show both strong variability with angle from the source, as well as some local increases in sound levels with increasing distance (e.g. directly to the south of the source; this was confirmed by the measurements). The difference between the two models is shown in Fig. 1c. Compared with RAM, the spreading law underestimates noise levels close to the source and substantially overestimates noise levels further from the source (the regions where there was no difference between the models include the sites where the field measurements were made). In this example, predictions for an EIA made on the basis of the spreading law model would underestimate noise exposure close to the source, which is the region where noise levels are highest (and risk of injury and disturbance is greatest). Furthermore, noise levels are overestimated further from the source (Fig. 1c), giving the misleading impression that a larger area would be affected. This clearly demonstrates why selection of an appropriate model is critical to making reliable assessments of potential noise exposure.

4. Input data

While it is critical to select an appropriate propagation model for the site, even a suitable model will not yield valid results if based on insufficient input data. The quality and resolution of the bathymetry, sediment, and water column data each affect the accuracy of propagation modelling, and any errors in the predicted sound level of the noise source will produce corresponding errors in the model output. In this section, we consider each of these factors in turn, and provide some illustrations of how inadequate input data can affect predictions of noise exposure.

4.1. Bathymetry

To set up a noise propagation model it is first necessary to choose the spatial extent and spatial resolution of the modelled area (the model domain). Most developments requiring a noise assessment occur in shallow water environments (e.g. <100 m), where the topography of the seafloor has a strong influence on sound propagation. This is because in shallow water, the main mechanism for sound propagation is

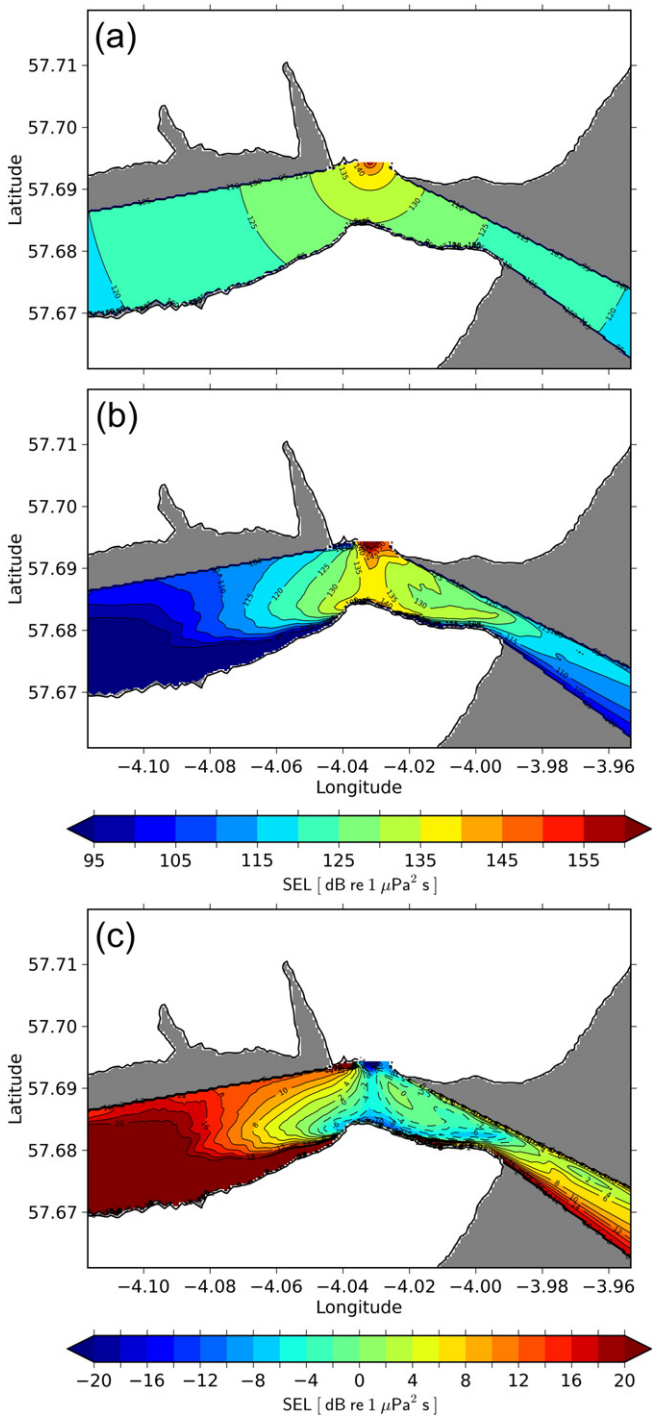

Fig. 1. Maps of predicted received level for a pile driving operation in the Cromarty Firth using two alternative propagation models. (a) Spreading law; (b) RAM; (c) difference (RAM minus spreading law).

the repeated reflection and scattering from the sea surface and seafloor boundaries. A key consideration is therefore the availability of bathymetric data with sufficient spatial resolution. Since the degree of sound scattering depends on the wavelength of sound (which is inversely related to the frequency), the required spatial resolution varies depending on the acoustic frequencies under consideration. As a rule of thumb, the spatial scale should normally be a small fraction of the Fresnel zone radius $RF = (\lambda R)^{1/2}$, where λ is the acoustic wavelength and R is the distance between the source and the receiver (Flatté et al., 1979; Katsnelson et al., 2012). For example, a ~10 km domain and a frequency range of 0.1–1 kHz (i.e. $\lambda = 1.5$–15 m for a sound speed of 1500 m/s) implies an RF scale from 120 to 400 m, which potentially indicates the need to use bathymetric data with a resolution of a few tens of metres or better. For many models, the underlying computations should in turn be made at a fraction of these scales in both range and depth.

4.2. Seabed

Together with the bathymetry, the seabed sediment characteristics also strongly influence the propagation of sound in shallow water due to the repeated reflections and scattering at the water/seafloor interface. Depending on the sediment properties, sound may be largely reflected by the seabed, scattered, or may be transmitted through the seabed to emerge back into the water column further along its trajectory. To model these effects, the most important parameters to consider are the sediment density, sound speed and acoustic attenuation.

The acoustic properties of different sediment types display a much greater range of variation than the acoustic properties of seawater, so a good understanding of these properties and their spatial variation is necessary for accurate modelling. Unfortunately, reliable data on the 3D geophysical structure and composition of the seafloor are often unavailable. Furthermore, even when such data are available, relating the geophysical properties of sediments to their acoustical properties can be challenging (Holland and Dettmer, 2013). Even if the propagation through sediments is neglected, and only the reflection back into the water at the seabed interface is considered, accurate computation of the reflected sound field still requires knowledge of the sediment properties over at least a few wavelengths in depth (Katsnelson et al., 2012), which in the case of low-frequency sound waves can be tens of metres. Various theoretical approaches are available for building an acoustic model of the seafloor, with many of them requiring the input of more than 10 geophysical parameters, some of which are difficult to obtain even in laboratory environments (Etter, 2013). A more empirical model based on measurements was developed by Hamilton over many years (Hamilton, 1972, 1976, 1980, 1987; Hamilton and Bachman, 1982) and has been widely used for practical modelling purposes.

To illustrate the consequences of uncertainties or errors in sediment data, we modelled sound propagation over an example domain using two different sets of values for sand found in the literature. The first representation (Sand A; Fig. 2a), is for a sediment sound speed of 1800 m s^{-1} (Hamilton, 1980), while the second (Sand B; Fig. 2b), is for a sediment sound speed of 1650 m s^{-1} (Jensen et al., 2011). The remaining parameters for the sediment properties were equivalent (density: 1.9 g/cm^3; attenuation: 0.8 dB/wavelength). The predictions were made for a region in the southern North Sea off the coast of Sizewell in eastern England, using the same parabolic equation model as shown in Section 3.

The acoustic properties of Sand B are closer to those of water than Sand A, meaning that for Sand B less sound energy is reflected at the water–seabed interface and more sound is scattered or absorbed into the seabed. This higher propagation loss for Sand B is evident in the lower sound pressure levels (Fig. 2b) compared to Sand A (Fig. 2a). The difference in predicted levels is around 8–10 dB at ranges between 1 and 5 km (Fig. 2c), and increases further with range.

This example demonstrates the difficulties in making a priori predictions of sound propagation using published data on the sediment acoustic properties, and highlights the need for calibration and validation of the models using field measurements, which is the topic of Section 5.

4.3. Water column

In addition to the bathymetry and sediment properties, the water column properties can have a substantial effect on sound propagation.

Two mechanisms affect sound propagation in the water column: variations in sound speed, and sound attenuation. The sound speed is determined by temperature, depth and salinity, which are influenced

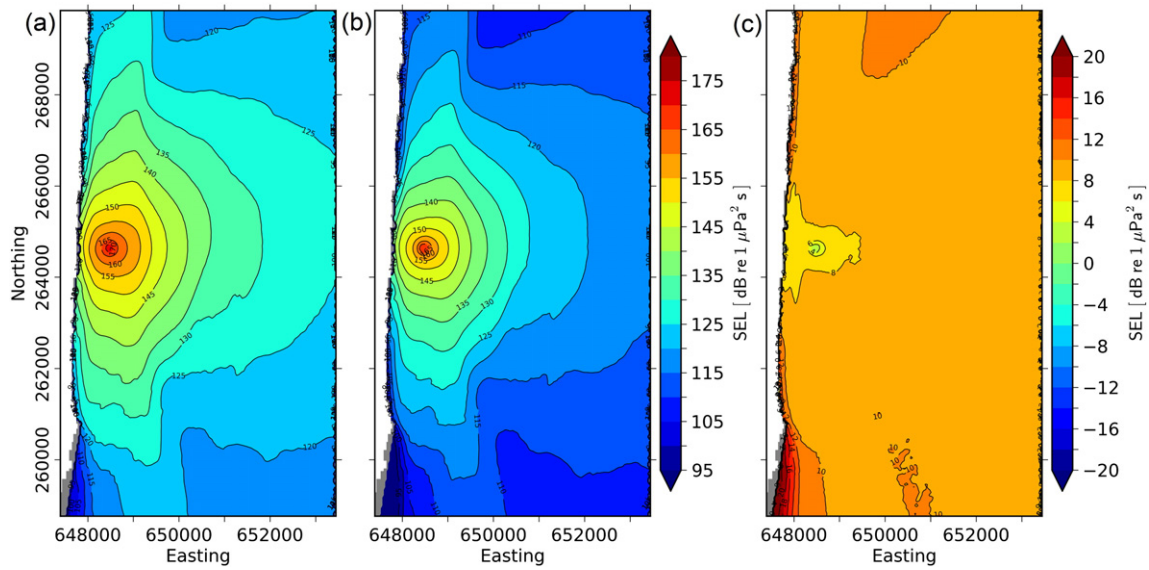

Fig. 2. The effects of seabed sediment properties on the sound exposure level (SEL) predictions in the water column: (a) predicted levels for bottom of sound speed 1800 m s^{-1} (Sand A); (b) predicted levels for bottom of sound speed 1650 m s^{-1} (Sand B); and (c) the difference between SEL predictions (A — B).

by local oceanographic conditions. The spatial variation in these parameters gives rise to gradients in the sound speed profile, particularly in the vertical axis. When acoustic waves travelling through the water column encounter changes in the sound speed they are refracted, bending either towards the surface or towards the seabed in the case of vertical variation. In shallow water and at short range, the spatial variations of the sound speed are typically small and their effects on sound propagation are generally much smaller than the effect of interactions with the seabed. However, seasonal temperature changes can have a substantial effect on propagation loss since the interaction at the water–seabed interface depends on the speed of sound in water (as well as the seabed properties). This is effect is discussed in more detail in Section 6. For the applications discussed here, sound speed profiles can be calculated with sufficient accuracy using simple formulas (Jensen et al., 2011). The second mechanism affecting sound propagation in the water column is sound attenuation, caused by scattering from inhomogeneities in the water column and absorption of sound energy by the water. This has a very small effect in the range of frequencies usually considered for EIAs. For example, in the 0.1–1 kHz band, typical attenuation values are between 0.004 and 0.05 dB/km (Thorp, 1967), and thus make a negligible contribution to propagation loss across typical domains.

4.4. Sea surface

Sound propagating in shallow water interacts not only with the seabed and water column, but also with the sea surface. A perfectly smooth water surface reflects nearly all of the sound energy, but as the sea surface roughens under the influence of wind, the intensity of these reflections can be reduced by scattering. Similarly to scattering at the seabed, the degree of surface scattering depends on the wavelength of sound, with shorter wavelengths (higher frequencies) subject to greater scattering losses.

A measure of the acoustic roughness of the sea surface is provided by the Rayleigh parameter $R = 2\pi H_{\mathrm{rms}} \sin\theta/\lambda$ (Brekhovskikh and Lysanov, 2003), where H_{rms} is the root-mean-square wave height, θ is the grazing angle (the angle between the path of the sound wave and the surface) and λ is the acoustic wavelength. The sea surface is considered to be acoustically smooth when $R \ll 1$, while $R \gg 1$ implies an acoustically rough sea surface. In a typical low-frequency ($\lambda > 1$ m), shallow water EIA scenario, where sounds propagates mainly at small grazing angles (e.g. $\sin\theta \approx 0.1$), and for moderate wave height (e.g. $H_{rms} \approx 1$ m), the typical values of the Rayleigh parameter are less than 1. This implies that losses of sound energy due to surface scattering are small, and are likely to be far less significant compared to the bottom losses due to interactions with the seabed. If sea surface interactions need to be modelled, data on wave height can be obtained directly from oceanographic models or derived indirectly from wind speed data.

4.5. Source level

The most important factor to reduce uncertainty in noise exposure predictions is the sound level of the noise source. The source level can be estimated using a physical or numerical model of the noise source, or by using field measurements of received level to back-calculate the source level using an appropriate propagation model (i.e. by making source level the subject of Eq. (1)).

Physical or numerical models have been developed for several common noise sources, including pile driving (e.g. Reinhall and Dahl, 2011; Zampolli et al., 2013; Lippert and von Estorff, 2014; Fricke and Rolfes, 2015), seismic airguns (e.g. Ziolkowski, 1970; MacGillivray, 2006), and shipping (e.g. Wales and Heitmeyer, 2002). Realistic models for such sources are necessarily complex, and may require a more detailed knowledge of the noise source and propagation environment than is available for the assessment. A more typical scenario is that measurements of a particular type of noise source from previous studies are used.

Estimates of source level based on field measurements generally assume that the noise source acts as a point source — an idealised point in space from which sound radiates with spherical symmetry. The source level can then be expressed as the sound level at a notional distance of 1 m from the source. If measurements are taken at a large enough distance, this point source approximation can still produce reasonable predictions even for large sources such as monopiles or ships. To calculate the source level, measurements of the sound level received at distance are combined with an estimate of the propagation loss between the source and receiver (using Eq. 1), yielding a source level estimate at a distance of 1 m. Given that this source level estimate is then used as input data to the model for the noise assessment, the quality of the predictions is doubly dependent on the accuracy of the propagation model. This issue is discussed in more detail in Section 7.

The units used to express the source level will vary with the type of noise source. The source levels of continuous noise sources such as shipping, dredging, or drilling should be expressed as a sound pressure level

(SPL), with units of dB re 1 μPa (some authors use dB re 1 μPa^2, though these are numerically equivalent; Merchant et al., 2015). Impulse sources such as pile driving and seismic airguns should have source levels expressed for a single pulse as either a sound exposure level (SEL) with units of dB re 1 μPa^2 s, or as a peak-peak or zero-peak SPL, with units of dB re 1 μPa (or dB re 1 μPa^2). For modelling purposes, it is problematic to use peak-peak (or zero-peak) SPL for impulse sources, since accurate modelling of this metric requires a detailed understanding of how the pulse becomes dispersed in the time domain, which is generally complex. By contrast, it is relatively straightforward to model SEL since it can be treated as a time-independent quantity.

5. Validation

As Fig. 2 demonstrates, uncertainties in model parameters can lead to significant variability in a priori predictions of noise exposure. To improve confidence and reduce uncertainty in the model, field measurements of sound propagation can be made to test and validate model predictions, and to optimise model parameters within physically realistic constraints. Here, we use an example dataset to illustrate how model validation can be conducted, and how even with reasonable assumptions, predictions of sound propagation can deviate substantially from actual measurements.

To validate model predictions of propagation loss at Sizewell (the North Sea site described in Section 4.2), field measurements of propagation loss were made using a seismic airgun sound source. Calibrated sound level measurements, corresponding to successive firings of the airgun, were taken simultaneously near the source (at ranges of 10–15 m) and along a series of transects ranging from 150 to 3500 m in water depths of 7–15 m, thus allowing calculations of propagation loss (the amount of sound energy that is lost over a particular propagation path). To account for tidal variation and slight variations in source position between firings, each measurement was modelled separately, using the particular water level, source and receiver positions (including depth) as inputs. The agreement between the predicted versus the measured sound exposure levels was then assessed in one-third octave frequency bands between 0.1 and 1 kHz.

Fig. 3a shows the agreement for the model with bottom type B discussed in Section 4. Bottom model B produced predictions with 58% of the points inside a ±10% envelope, and an average RMS error of 17.2 dB, or 16.1%. However, the pattern of errors clearly shows under-prediction of SEL in the lower frequency bands and over-prediction in the higher frequency bands (Fig. 3a), suggesting that the model does not accurately reflect the frequency dependence of propagation loss. The cause of this error is unlikely to be the bathymetry data, since while the bathymetry has a strong influence in shallow water, this was well defined for the domain. The likely cause of this error is therefore the sediment properties, which are also an important factor in shallow water environments.

To optimise the model, a correction was made to the frequency dependence of sediment attenuation. A depth-dependent variation of the sediment properties was introduced, as detailed in Hamilton (1980), which corrected the underestimation at low frequencies. Then, to model the observed variation with frequency, a non-linear acoustic attenuation scaling factor was applied, which scaled with $f^{1.8}$ instead of the original linear dependency with f considered by Hamilton. The exponent of 1.8 was arrived at through an iterative process, and agrees with studies showing that in granular sediments such as sand, the attenuation dependence tends to f^2 at low frequencies below 1 kHz (Biot, 1962; Katsnelson et al., 2012; Holland and Dettmer, 2013). This optimised model resulted in substantially improved predictions across the frequency spectrum, with 95% of data points within the ±10% envelope and an average RMS error of 6.2 dB, or 5.4%.

Fig. 4 shows how the noise levels predicted by the a priori and validated models differ over the study site across all frequencies. The a priori model underestimated noise levels by up to 6 dB within ~1–2 km of the source, and overestimated by 5–20 dB outside this area. This pattern can be explained by the previous observation of SEL under-prediction in the low-frequency bands, which dominate in the source spectrum but do not propagate well in this very shallow environment, meaning that the over-prediction in the higher frequency bands begins to dominate as distance increases.

It should be noted that the results shown in Fig. 3 were obtained with a model that did not include the effect of the sea surface waves. To test the effect of surface scattering from waves, contemporaneous data on local wave height (with $H_{rms} \approx 0.7$ m) were included in the computations. The wave model resulted in similar RMS errors to the non-wave model, but with a slightly reduced sediment frequency attenuation exponent of 1.75 instead of 1.8. This can be understood as the non-wave model compensating for the effect of sea surface scattering with a slight increase in the seabed attenuation, yielding comparable results.

As this example illustrates, the process of model validation depends on the interpretation of model agreement and the application of suitable modifications to the model where required. There are no 'hard-and-fast' rules for this procedure: each validation should be based on detailed analysis of the model agreement with observed data, and informed by physical interpretations of the model parameters. It is particularly important that the model agreement is assessed at a range of frequencies, since broadband analyses (which represent the sound

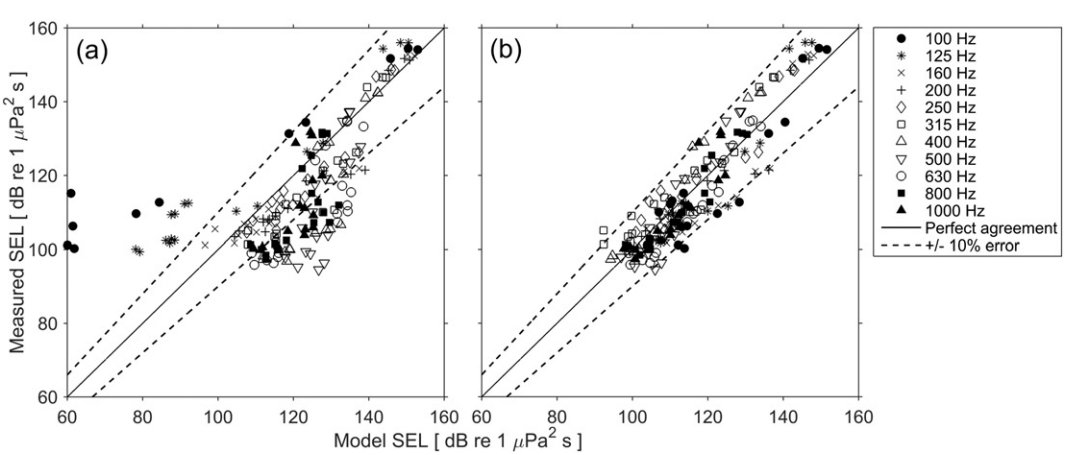

Fig. 3. Modelled versus measured SEL for all 1/3 octave bands in the interval 100–1000 Hz, for (a) a priori model with sandy bottom B and (b) the optimised and validated model.

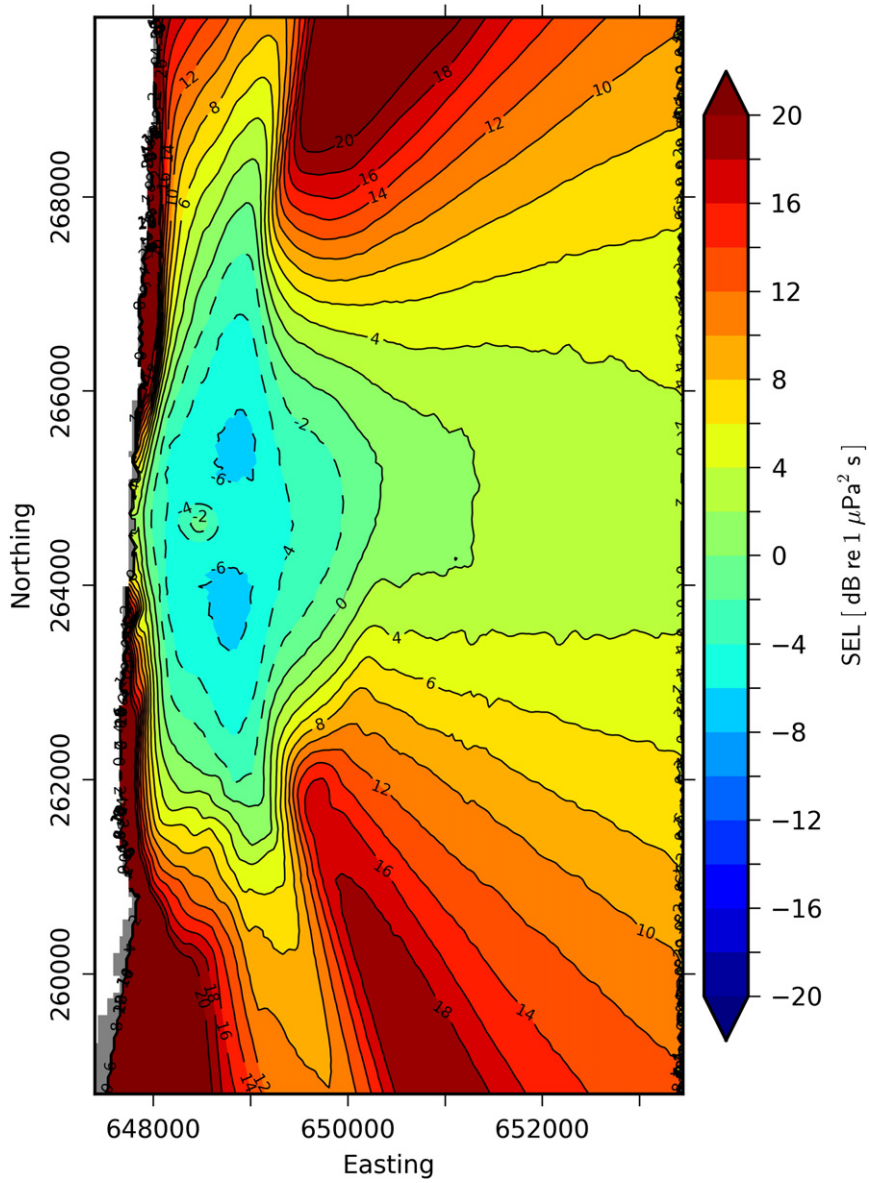

Fig. 4. Difference in predicted levels between a priori model (not optimised) and model optimised using field measurements. Negative values indicate an underestimation of received sound exposure by the a priori model.

level over a swathe of frequencies as a single number, as in Fig. 4) can disguise substantial deviations at particular frequencies, as well as systematic disparities across the frequency spectrum.

6. Application

Once the model has been set up appropriately (and, where possible, validated), consideration should be given to the time-varying environmental conditions that are expected during the proposed activity. If these differ from the parameters used in the validation scenario (or a priori model conditions), an updated model setup may be required. Among the most important factors are the effect of tidal water level variation and that of seasonal sea temperature variation, both of which are likely to be relevant to practical EIA scenarios. Here, we briefly illustrate the effect that these parameters can have on model predictions.

6.1. Tidal effects

In shallow environments, tidal variations can represent a significant fraction of the actual water depth and thus significantly influence sound propagation. For example, in the domain shown previously in Sections 4 and 5, the bathymetric depth is ~8 m in the source area and less than 30 m over the entire domain, while the maximum tidal variation is ~3.3 m. To examine the sensitivity of the validated model to tide level, we ran scenarios for both mean seawater level and high water level (1.3 m above mean sea level). The high water level case (Fig. 5a) has higher predictions than the mean sea level case (Fig. 5b), due to better propagation in the low-frequency bands. This effect is due to low-frequency 'cut-off' in shallow water, which has a greater effect as water depth decreases (Jensen et al., 2011). The increase in predicted SEL is about 5–20 dB (Fig. 5c) with the greatest increases where noise levels are lower.

6.2. Temperature effects

As discussed in Section 4, water temperature can influence sound propagation through changes in the speed of sound in water, which has a direct effect on the interactions at the water–seabed interface. As an illustration of this effect, Fig. 6 presents predictions for cold water (8 °C, typical March values) and warm water (18 °C, typical

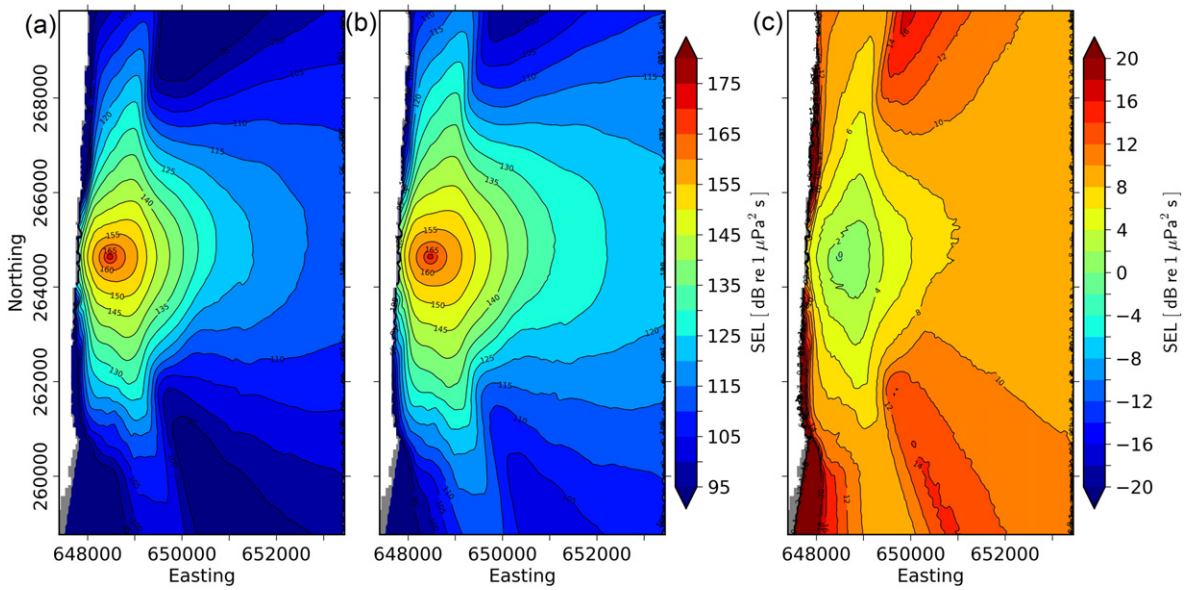

Fig. 5. The effects of water level on sound pressure level predictions: (a) predicted SEL for mean sea level; (b) predicted SEL for increased water depth (1.3 m above mean sea level); and (c) the difference between SEL predictions (a minus b).

August values) for the Sizewell example. The 10 °C increase in temperature corresponds to a 33 m s^{-1} increase in the speed of sound in water, which reduces the efficiency of sound reflections at the water–seabed interface meaning more energy is absorbed into the seabed. In other words, the warmer water temperatures lead to poorer sound propagation. This is shown clearly in Fig. 6, where predicted SEL was 5–10 dB greater in the cold water scenario at distances greater than 2 km from the source.

7. Consequences of errors in propagation modelling

The key consideration for decision makers in the EIA process is whether levels of noise exposure may present an unacceptable risk of harm to species of interest. In relation to noise modelling, the principal concern is therefore the extent to which errors or uncertainties in the model affect predictions of noise exposure. This section summarises how modelling errors affect estimates of noise exposure in EIAs, and illustrates the sometimes counterintuitive consequences.

The more straightforward scenario is that in which the source level has been estimated using a physical or numerical model (see Section 4.5), as shown in Fig. 7a. In this case, over- or underestimates in the source level lead directly to respective over- or underestimates in received level. The inverse is true for errors in propagation loss: too much propagation loss leads to an underestimate of received level and vice-versa. This follows directly from the relationship between received level, source level, and propagation loss given in Eq. 1.

The picture is more complicated when measurements have been used to estimate the source level (Fig. 7b). Since a propagation loss model is used to estimate the source level, over- or underestimates of propagation loss lead to errors in this input data. Assuming that the model has been set up such that the model predictions match the field measurements at the distance they were made (point M in Fig. 7b),

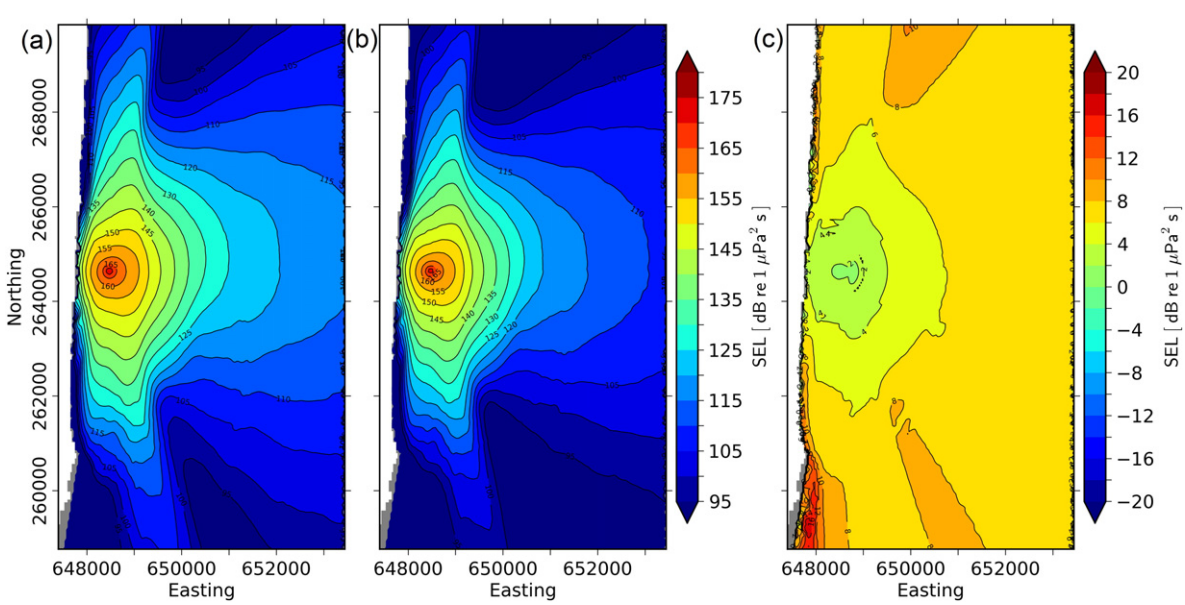

Fig. 6. The effects of seasonal temperature changes on the sound pressure levels predictions: (a) predicted SEL for typical March conditions (8 °C), (b) predicted SEL for typical August conditions (18 °C) and (c) the difference between SEL predictions (a minus b).

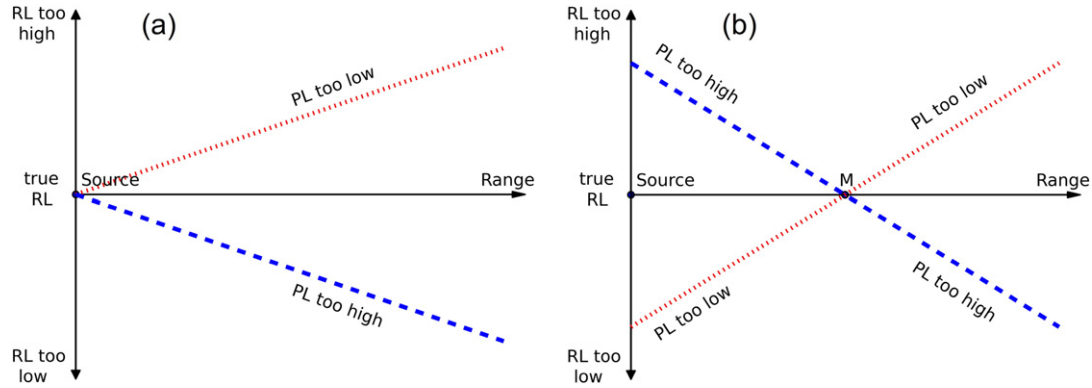

Fig. 7. The effect of systematic errors in propagation models on noise level predictions. (a) Source level model. (b) Measured source level.

errors in propagation loss lead to a pattern of errors in received level as shown in Fig. 7b. If the propagation loss is too high, more sound energy is estimated to have been lost between source and receiver than was the case, leading to an overestimate in the source level (and in the received level between point M and the source). At ranges greater than *M*, this same overestimate in propagation loss results in an underestimate of received level, since more energy is predicted to be lost than the true value. It follows that the inverse effect is seen for underestimates of propagation loss (Fig. 7b). This effect was clearly illustrated in Section 3, where the spreading law model under-predicted propagation loss compared to the parabolic equation model, leading to underestimates of noise exposure near the source and overestimates at distances beyond the measurements.

For simplicity, we have assumed that propagation losses are either over-predicted or under-predicted uniformly over the entire model area. In reality, both over- and under-prediction may occur in the same model, particularly in complex environments. That said, even the more complex computational models can introduce systematic positive or negative errors in propagation loss, either through errors in input parameters (see Section 4), or by disregarding temporal effects such as tide level and temperature (see Section 6).

8. Outlook

Errors and uncertainties in noise modelling can lead to significant pitfalls in the EIA process. Underestimates of noise exposure lead to an underestimation of the risk of injury and disturbance to marine life. This is of particular concern in the vicinity of the noise source, where these impacts are most likely to be acute. On the other hand, if noise exposure is overestimated over a wide area, otherwise acceptable operations could be denied regulatory consent on the basis of inaccurate predictions. This paper has reviewed and assessed the many factors that affect predictions of noise exposure in an EIA context, with the aim of clarifying and summarising the science underlying noise modelling for the benefit of regulators, stakeholders, and practitioners. To allow an informed appraisal of the risk of noise-related impact, it is then critical that EIAs clearly state the underlying assumptions and scientific basis for noise exposure predictions. This applies particularly to the characterisation of the noise source, to the modelling of propagation loss, and to uncertainties in the input data relied upon in the model.

The field of underwater noise assessment is still relatively new, and uncertainties in assessing risk to marine life are high due to the complexity of animal responses to noise pollution (Slabbekoorn et al., 2010; Ellison et al., 2012; Thompson et al., 2013). However, the study of sound propagation is well established and understood, and need not present a significant level of uncertainty if carried out according to best practice. An aspect of noise modelling which does present considerable uncertainty is the characterisation of noise source levels. Many sources of underwater noise have yet to be well described by measurements, particularly novel sources such as wave and tidal energy devices (Frid et al., 2012). While sophisticated physical and numerical models to describe sources such as impact piling have been developed recently (e.g. Reinhall and Dahl, 2011; Zampolli et al., 2013; Lippert and von Estorff, 2014; Fricke and Rolfes, 2015), they are not yet in wide use for EIA applications.

Two further elements of noise modelling warrant further research in order to reduce the uncertainty associated with underwater noise assessments. First is the application of modelling techniques to predict the propagation of sound in the time domain. Current models used in EIAs are based on modelling the overall sound energy as it spreads away from the noise source. However, the risk of acute auditory injury is closely linked with the temporal structure of sound, and in particular the sharpness of peaks in sound pressure caused by impulsive sources (e.g. impact pile driving or seismic airguns). As these pulses propagate away from the source, the sharp peaks in sound level become more dispersed, and present less of a risk of auditory injury relative to the sound energy contained within them. Techniques developed for time-domain modelling of sonar signals could be applied to this problem to better understand the risk associated with impulsive noise sources. The second area of study is the modelling of particle motion propagation. Current models applied in EIAs consider only the sound pressure component of sound, which is the means by which mammals hear. However, the primary mechanism by which fish and invertebrate species detect sound is through another component known as particle motion (Popper and Fay, 2011; Morley et al., 2014). Levels of sound pressure and particle motion can deviate substantially in the region close to noise sources and in shallow water (Hawkins, 1986), and so techniques to specifically model this component of sound are needed to better predict the potential impact of noise-generating activities on these animal groups.

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