A multi-layered risk estimation routine for strategic planning and operations for the maritime industry

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Abstract

Maritime regulators and port authorities require the ability to predict risk exposure for strategic planning aspects to optimize asset allocation, mitigate and prevent incidents. This article builds on previous work to develop the strategic planning component and introduces the concept of a multi-layered risk estimation framework (MLREF) for strategic planning and operations. The framework accounts for most of the risk factors such as ship specific risk, vessel traffic densities and met ocean conditions and allows the integration of the effect of risk control option and a location specific spatial rate ratio to allow for micro level risk assessments. Both, the macro (eg. covering larger geographic areas or EEZ) and micro level application (eg. passage way, particular route of interest) of MLREF was tested via a pilot study for the Australian region using a comprehensive and unique combination of dataset. The underlying routine towards the development of a strategic planning tool was developed and tested in R. Applications of the layers for the operational part such as an automated alert system and sources of uncertainties for risk assessments in general are described and discussed along with future developments and improvements.

Keywords: Total risk exposure, binary logistic regression, spatial statistics, incident models, uncertainties, strategic planning, operational alerts, drift groundings, collisions, powered groundings, prediction routines

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1. Introduction

Incidents in shipping can lead to high costs and pollution damages to society. These costs vary substantially as demonstrated by some selected examples such as $37 Million (*Sea Empress, 1996*), $120 Million (*Shen Neng One, 2010)*, $ 1.5 billion (*Costa Concordia 2012*) or $ 9.5 billion (*Exxon Valdez, 1989*). The overall goal of any regulatory authority such as maritime administration or port authority is to assess and predict risk exposure in order to enhance the selection and deployment of risk control options (RCO's) such as for instance vessel traffic management, improved surveillance, aids to navigation, pilotage, inspections and surveys, emergency responses. This allows improved asset allocation at the strategic level but also enhance surveillance to prevent incidents from happening at the operational level.

We build on the work of Van der Hoorn and Knapp (2015) and introduce the multi-layered risk estimation framework (MLREF). MLREF consists of input data, intermediary data layers, routines, algorithms and end user interfaces such as the strategic planning tool (SPT) or an automated alert system. With a fully automated calculation process, maritime stakeholders are able to run prediction scenarios of plausible traffic increases or changes in the composition of the world fleet and calculate risk exposure for strategic planning aspects via the use of a *strategic planning tool (SPT*). Implementation aspects are crucial if the proposed methods should be used in practice and this paper therefore covers both aspects of interest – that is, the medium to long term aspect for strategic planning and the real time or near real time aspect for operational activities such as *automated alert systems* in order to avoid costly accidents. Risk exposure endpoints are collisions, powered and drift groundings leading to a very serious and serious incidents as well as candidates (irrespective of seriousness) but can be extended in the future – in particular the integration of estimating risk exposure in monetary terms (Vander Hoorn and Knapp, 2015).

Current approaches for risk assessment in shipping show limitations. Application areas are either geared towards semi real-time operational aspects (Hueffmeier et al., 2012) or small areas using a micro-level approach or medium to long term strategic planning aspects with limited prediction ability (DNV, 2013, BRISK, 2012) since changes in location and magnitude of risk given future traffic scenarios are not quantified. Neither line of approach allows the integration of fully automated routines in order to quantify risk exposure. Most importantly, risk is primarily estimated by modelling the geometry of the traffic and ignores the individual safety qualities of vessels. As such, vessels are treated equally which is unrealistic given that safety qualities of vessels can vary considerably (Heij and Knapp 2012, Heij et al. 2011, Knapp 2006) and are the reason why port state control inspections or industry vetting inspections exist. If incident data are used in current approaches, it is not combined from various sources and biases can therefore influence the validity of results.

Another shortcoming of current methods is that the underlying location specific environmental criteria such as the effect of wind, wave and currents are omitted due to the complexities involved in quantifying their effect on risk exposure. Furthermore, uncertainties in the estimates are not identified nor quantified (Merrick and van Dorp, 2006). Previous approaches to model location specific probabilities of oil spills for instance provide very different results (Goerlandt and Stahlberg, 2011) and demonstrate the difficulty in providing reliable answers. The lack of understanding of the sources and magnitude of uncertainties provides difficulties for regulators to make policy decisions in order to reduce risk to an acceptable level of residual risk.

The paper first provides a short introduction of MLREF followed by the theoretical framework and the results of a pilot project with the Australian Maritime Safety Authority (AMSA) indicating what has been developed so far for three regions of interest – the Great Barrier Reef (GBR), the North West (NW) and the South West (SW) regions of Australia (refer to section 5 for more details). The report will end with a description of outstanding items and suggestions for improvements.

2. Description of components and high level functionality aspects of MLREF

Based on Vander Hoorn and Knapp (2015), total risk exposure can be described as the combination of risk layers as follows: 1) ship specific risk as proxy to safety quality, 2) vessel traffic densities, 3) location specific physical environmental parameters such as wind, wave, currents and bathymetry, 4) other environmental factors such as sensitivities to pollution; and 5) intervention effects of risk control options (RCO) which can be deployed to mitigate risk such as eg. pilotage, emergency towing tugs, VTS, SRS, navigational aids, inspections. Total risk exposure is defined as the integration of the above described risk layers in order to assess and predict risk exposure for a given area of interest.

MLREF builds on this approach and creates layers of the risk based on data feeds and their derivatives (eg. histories, calculated variables) form the basis for the development and implementation of various *risk algorithms* (in the case of drift candidates) or *risk formulas* (based on statistical models in the case of quantifying safety qualities of vessels or targeting ships for PSC inspections). Once the formulas (algorithms) are implemented dynamically, either the probabilities and/or the drift detection algorithm can be used to create *active or passive alerts* in conjunction with the respective GIS layers.

One major difference to other approaches is that in combining the first two layers, we capture the individual safety quality of a vessel in addition to vessel traffic densities rather than estimating risk based on the geometry of vessel traffic. It is believed that 80% of all navigational incidents are somehow related to human error (Hansen, 2007), hence the safety quality of a particular vessel is assumed to be more important in most incident cases.

To *increase awareness of potential dangerous situations* and *to reduce response time* in case of an emergency situation, the components of the framework can be used to assist a monitoring and alert system. Figure 1 provides a simplified illustration of the concept. For each vessel entering an area of interest, a ship specific risk profile (proxy to safety quality) can be estimated, attached and monitored by the system. If the vessel is found to be a medium or high risk vessel (eg within the 5 or 10% of the world fleet), the surveillance system can put a '*passive alert or more frequent watch'* of the vessels trajectory or activity. If any vessel shows any abnormal behaviour (eg drifting), its status can change to an '*active alert'* and a message is send out to take action. In the case of a drift grounding candidate of a high risk vessel, abnormal behaviour can automatically trigger a drift trajectory simulation to increase awareness of potential dangerous situations and to estimate the critical time to shore – that is until the vessel grounds. This can also be integrated with a simulation for potential oil pollution if the vessel is projected to ground within a certain time frame.

For strategic planning, where the time frame is longer into the future (eg next 5, 10, 15 years), change in risk exposure over longer time frames is compared to the chosen baseline by running prediction scenarios using a *strategic planning tool* (SPT). The end user can run prediction scenarios and perform sensitivity analysis given the effect and combination of control options (RCO) to find the best combination to mitigate risk, save money with improved asset allocation or make policy decision (eg. divert traffic). The developed routine should provide an estimate of the uncertainties when possible.

The risk exposure endpoints at this stage are collisions, powered and drift groundings and can be measures in various ways such as probabilities, expected numbers of incidents and the monetary value at risk as proxy to consequences (Knapp and Heij, 2016). Endpoints can be extended in the future to include loss of life or pollution or end points of particular interest to domestic vessels.

The remainder of this article will provide the theoretical framework of the development of the routine for strategic planning with the aim to develop a *strategic planning tool* in the future. In this article and in particular the translation of arrival forecasts into estimated number of incidents via a route network and voyage database and the integration of the met ocean layer for drift groundings was of main interest. The routine was developed within a pilot project in conjunction of the Australian Maritime Safety Authority (AMSA) and relevant aspects are described concerning the pilot project are therefore described.

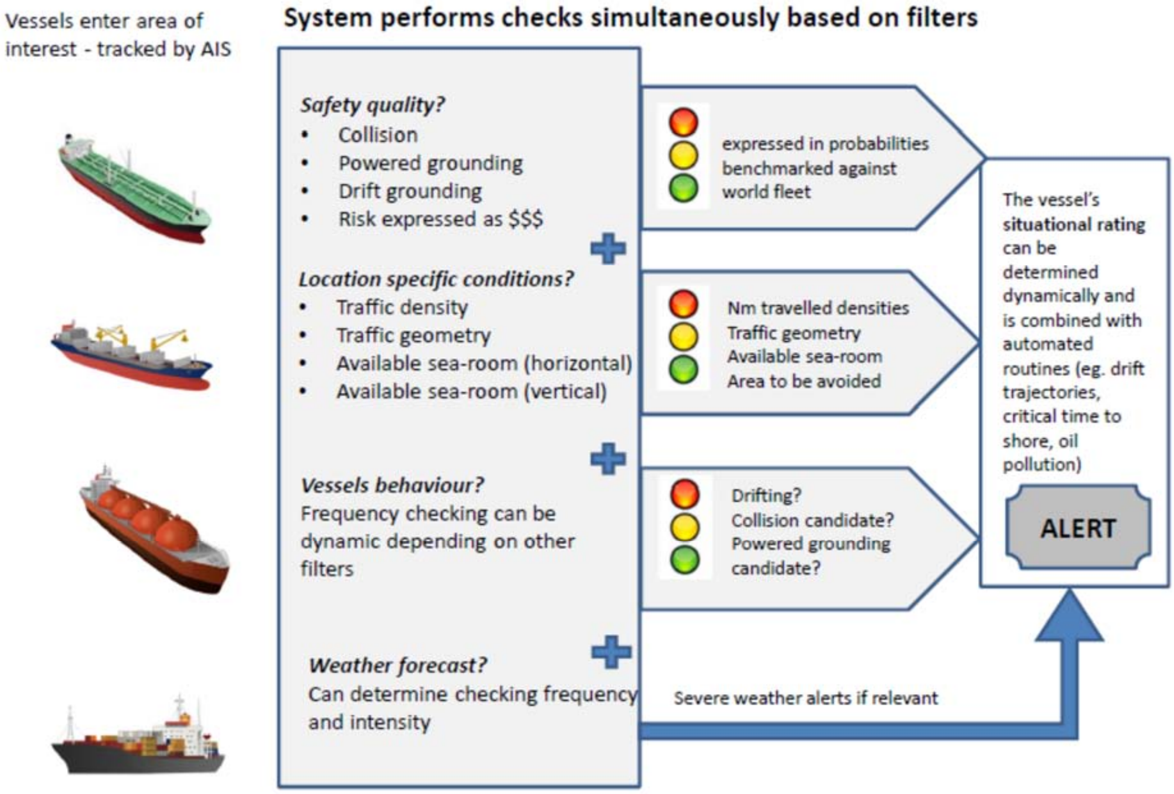

Figure 1: MLREF alert system (high level description)

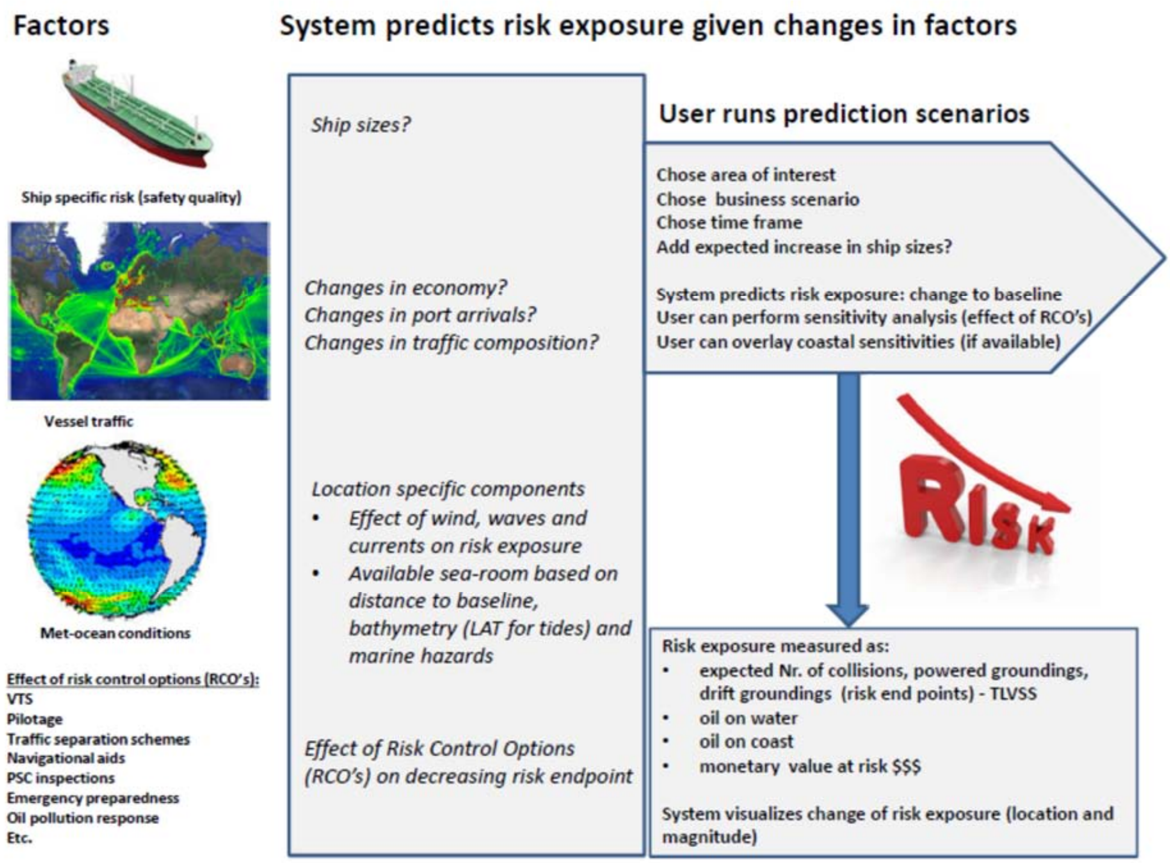

Figure 2: MLREF: strategic planning tool (high level description)

3. Theoretical framework for traffic and risk prediction routine for strategic planning

We build on previous research of Vander Hoorn and Knapp (2015) which provides a routine to combine ship specific risk and vessel traffic densities based on nautical miles travelled. We extend the routine to integrate the met ocean layer and by translating increase in ship arrivals into changes in risk exposure across the traffic route network of a particular region. This is needed in order to run prediction scenarios and to perform sensitivity analysis using a strategic planning tool in the future.

The aim is to evaluate current risk and to predict how the location and magnitude of risk exposure will change given an increase in traffic. The focus is on aggregating risk across total traffic (either current or under some counterfactual). As mentioned earlier, risk exposure endpoints, collisions, powered and drift groundings leading to a very serious and serious incident as well as candidates are included but can be extended to include other endpoints in the future.

3.1. Basic concepts

Vander Hoorn and Knapp (2015) present a method which allows aggregation of individual ship specific risks with total traffic densities measured as distance travelled to derive total risk exposure across large areas. Ship specific risk as proxy to safety quality is based on Knapp (2006, 2011) using binary logistic regression and a combination of data sources (IMO, IHS Markit, LLIS, AMSA) combining a five year dataset of ship particulars of the world fleet, their changes over time, global incident and PSC inspections. Approximately 500 variables have been tested and separate models are estimated for each incident type and seriousness if possible. Incident seriousness is classified based on IMO definitions (IMO, 2000). Please refer to Appendix A for a high level summary of the logit models.

Traffic data is matched against a route network which provides the entry/exit points of the area of interest and accounts for all possible routes of the entry/exit points to major points capturing around 80% of total traffic. A method for generating a voyage database was tested for the pilot project and a high level description of the voyage database and Route network is provided in Appendix B. A spatial adjustment can also be considered if the data are available to reflect relative differences in risk between areas. More formally, this is implemented by first defining risk for an individual voyage p_{ij} as:

$$p_{ij} = p_i \times \frac{d_{ij}}{E[d_i]} \tag{1}$$

where:

p_i *is the annual accident probability for vessel i (based on a vessel with ship particulars equal to that of vessel i).*
d_{ij} *is the nautical miles travelled during voyage j of vessel i*
$E[d_i]$ *is the expected total nautical miles travelled for vessel i (based on the expected nautical miles travelled for the vessels of this type)*

Note that distance travelled is used here as a proxy for calculating risk exposure. In principle, there will be many metrics that can be considered in this step, days at sea, frequency of collision candidates, etc. Defined in this way, the assumption is made that the effect of ship specific risk factors for vessels observed in the study region is the same as the global ship-level risk but scaled (down) according to the fraction of traffic exposure. In other words, a *baseline risk* for a given level and type of traffic based on incident models estimated on global incident data based on Knapp (2006, 2011) is defined and applied at the individual voyage level. The rate of accidents of ship type *k* can be obtained as

$$\lambda_k(s) = \sum_{j \epsilon k} p_{ij}(s) \tag{2}$$

where $p_{ij}(s)$ is the baseline probability for voyage *j* of ship *i* having an accident at location *s*. Spatial differences in risk between areas could be incorporated by

$$\lambda_k(s) = \sum_{j \epsilon k} p_{ij}(s) \times RR_{sp}(s) \tag{3}$$

where $RR_{sp}(s)$ is an estimator for the spatial rate ratio at location s. At this stage, a spatial rate ratio for collisions and powered grounding taking into account location section traffic conditions still needs to be developed and a separate project is currently dealing with this aspect. For drift groundings, section 3.3 deals with the integration of the spatial rate ration as the location specific met-ocean layer which is needed for more refined risk assessments at the micro level. The pilot project presented here described provides both solutions – one for the macro level and a more refined one for the micro level.

3.2. Traffic density under counterfactual scenario

Let $D_{kp}(s)$ represent a baseline traffic density quantified as total nautical miles travelled (per 1000 vessels) at location *s* after aggregating across all *j* voyages of ship type *i* into/out of port p[3]. Then a traffic density under a counterfactual scenario can be defined as

$$D_k^c(\mathrm{s}) = \sum_p D_{kp}(s)\, n_{kp} RR_k^c \qquad p = 1 \ldots P, P+1 \qquad (4)$$

where $D_k^c(s)$ represents the traffic density at location *s* under counterfactual scenario *c* for ship type *k* and which can be derived as the product sum across all ports of the port level density $[D_{kp}(s)]$ the number of voyages for ship type *k* $[n_{kp}]$ to/from a port (in multiples of 1000), and the relative rate of change in numbers of voyages for ship type *k* $[RR_{kp}^c]$ between the baseline traffic density and the counterfactual scenario which is estimated from arrival forecast which can be provided externally.

In equation 4, *P+1* represents the case whereby a vessel enters the area of interest but then bypasses all major ports defined on the route net. The traffic density for *P+1* represents a relatively small proportion of all voyages but is needed here to capture total vessel activity.

The computation is carried out by further stratifying by 1) into ports, 2) out of ports, and 3) within ports. Whilst it is not necessary to perform these calculations with this additional level of stratification, the distinction was useful for better understanding how risk could be further broken down at the port level.

The counterfactual traffic density is not calculated at the route level, i.e. it is based on scaling total traffic flows at the port level. In theory, it would be possible to extend the method described here so that any differences in relative changes at the route level can be reflected in the counterfactual density. However, this would only be necessary if general traffic patterns along major routes for a selected port/ship type pair were expected to change at different rates. Preliminary analyses of data provided via the pilot project did not reveal that for Australia. In the future, estimation of the baseline traffic density could be established with a larger baseline period such as 3 to 5 years instead of one year only as used in the pilot study. This would also give a more accurate assessment of risk.

Under the above approach, new routes could be added and existing routes could be removed from evaluation of the counterfactual traffic density. The total density under the counterfactual scenario can then be derived by:

$$D^c(\mathrm{s}) = \sum_k D_k^c(s) \qquad (5)$$

Under a counterfactual traffic scenario (e.g. traffic in 2025), the rate of accidents $\lambda_k^c(s)$ for ship type equal *k* can be obtained by:

$$\lambda_k^c(s) = \begin{cases} \int_s \lambda_k(s) \times \left[1 + D_k^c(\mathrm{s}) - D_k(\mathrm{s})\right] ds & \text{for groundings} \qquad (6) \\ \int_s \lambda_k(s) \times [1 + D^c(\mathrm{s}) - \mathrm{D(s)}]^\gamma ds & \text{for collisions} \qquad (7) \end{cases}$$

where:

[3] Double counting vessels travelling between ports is avoided in this calculation, i.e. a vessel that travels from one port to another is not counted twice as both an arrival and a departure

$D(s)$ is an estimator of baseline (current) traffic density at location s summed across all ST
$D^c(s)$ is an estimator of counterfactual (future) traffic density at location s summed across all ST
$D_k\ (s)$ is an estimator of baseline (current) traffic density at location s for ST equal k
$D_k^c(s)$ is an estimator of the counterfactual (future) traffic density at location s for ST equal k

Finally, the overall accident rate at location s for the counterfactual scenario can be obtained as:

$$\lambda^c = \sum_k \lambda_k^c\,(s) \tag{8}$$

The parameter γ links a change in traffic density to a change in risk and this is commonly set to be equal to two. This assumption is inherently made by most maritime risk assessments whereby collision risk increases according to the square of the change in traffic over time (DNV, 2013, BRISK, 2012). The temporal relationship between changes in traffic and change in risk may be more complex than this, however, and the same assumption is used as a starting point based on available data and research carried out in this area. Ideally, this assumption should be tested using for instance time series data of a longer period.

3.3. Integration of met ocean layer for drift groundings – micro level

Estimates for drift grounding at the macro level such as the whole of the EEZ of Australia or large regional areas (eg. North West, Great Barrier Reef Area) can be based on Vander Hoorn and Knapp (2015) where calculations consist of combing layers 1 and 2 (ship level probabilities and traffic density) which provided credible estimates consistent with historical data at an overall regional level.

Greater caution needs to be given when interpreting these estimates at the local level where the method would need to be further refined if a valid estimate for rate of drift grounding were required at a specific location within the GBR such as a passage or particular route across a smaller area. This is due to the unique geometry of the traffic as well as the uncertainty of other location specific environmental factors such as the effect of wind, wave and currents on the hull of a drifting the vessel.

The general idea of how this might be implemented was introduced by Eide et al (2007) where the frequency of drift grounding is modelled to be the product of the frequency of ship drift candidates (F_{drift}) and the probability of grounding given that the ship is adrift ($P_{grounding|drift}$):

$$F(x, y, t) = F_{drift} * P_{grounding|drift}\,(x, y, t) \tag{9}$$

More formally, the calculations for probability of grounding are carried out given the three distributions, f_{TRT}, f_{TTS} and f_{SRT}, and derived analytically through integration over time as follows:

$$\begin{aligned} P_{grounding|drift} = 1 &- \int_{s=0}^{\infty} f_{TTS}\,(s) \int_{t=0}^{s} f_{SRT}\,(t)\ \mathrm{dt\ ds} - \int_{s=0}^{\infty} f_{TTS}\,(s) \int_{t=0}^{s} f_{TRT}\,(t)\ \mathrm{dt\ ds} \\ &+ \int_{s=0}^{\infty} f_{TTS}\,(s) \int_{t=0}^{s} f_{SRT}\,(t)\ \mathrm{dt\ ds} \times \int_{s=0}^{\infty} f_{TTS}\,(s) \int_{t=0}^{s} f_{TRT}\,(t)\ \mathrm{dt\ ds} \end{aligned} \tag{10}$$

where:

The "tug-response-time" probability density function (f_{TRT}): defines the distribution for tug response time.
The "self-repair-time" probability density function (f_{SRT}): defines the distribution for time it takes for a vessel to repair
The "time to shore" probability density function (f_{TTS}): defines the distribution for time until a vessel grounds with a reef or shore-line, given that it has lost power/steering, and assuming it is unable to repair itself or be rescued by a tug. In the context of this application, f_{TTS} depends on the position of break-down relative to obstacles/shore, winds, currents, other environmental conditions at the time of break-down, and type of vessel.

In order to test integration of the above into the prediction routine, some assumptions were made in the pilot project for AMSA and alternative starting points for F_{drift} were evaluated and are described along with the pilot project results.

3.4. Integration of the effect of risk control options

The calculations above are carried out firstly without consideration to presence of risk control options (RCOs). Under this definition, a base case scenario is estimated which can then be re-estimated after applying the effect of an RCO (or joint effect of multiple RCOs combined). Estimates for the effect of RCOs are a topic for research and are location specific using expert knowledge elicitation. For the purpose of illustrating the integration of this layer in the pilot project, results from earlier work (DNV 2013) are used but can be replaced once this layer is fully completed. The next section will provide a discussion about uncertainties relevant for MLREF in order to highlight some aspects which are normally not considered in maritime risk assessments.

3.5. Discussion on uncertainties

One problem with current approaches in maritime risk assessment is that the decision maker is led to believe that the results are definitive and in no way uncertain. The general concept of uncertainty of risk assessment is well established in the literature (Hayes, 2011) including the various types of uncertainties. The majority of approaches to maritime risk assessment do not attempt to quantify uncertainty (Merrick and van Dorp, 2006, Eide et al., 2007). Furthermore, in the few cases where uncertainty intervals are provided, authors take great care to acknowledge the wide range of sources and assumptions made and highlight that complete quantification of uncertainty is not possible.

Uncertainties arise from input data, parameter estimates, as well as simplifications and assumptions used in the modelling approach. If qualitative methods are used based on subjective judgement, additional challenges arise which is mostly relevant for estimating the effects of risk control options (RCO's). These could be due to different perceptions, beliefs and experiences and cognitive biases (Pidgeon et al. 1992, Rohrmann 1994, Kahneman & Tversky 1984, Fischhoff et al. 1977). In order to handle uncertainty within the general framework proposed here, uncertainty arising from each source would first need to be considered separately. Several sources of uncertainty that should be considered under the framework presented earlier are described below.

Describing current traffic activity within major regions is of interest to maritime administrations in an operational context as well as for longer term planning purposes. The risk assessment presented here is based on one year of AIS data and a next step that would be reasonably straight forward is to apply the method to a longer time series of AIS data in order to gain a better understanding of spatial-temporal variations in traffic behaviour. This could be undertaken at a relatively fine geographical mesh level and then aggregated up to any area of interest. It is unlikely there would be a marked variation in total distance travelled yearly but is would be useful to examine variation at the sub-regional level (or for major routes) and/or specific subgroups of the vessel types.

Ship specific risk probabilities used in this framework are estimated based on a combined dataset consisting of global incident data and global world fleet data based on Knapp (2006, 2011) using statistical models. A related matter concerns the assumption being made when making extrapolations into the future. Logically, it's likely that risk profiles will also change over time. Not only because composition of the vessel cohort will change but also because underlying risk for vessels with the same ship particulars will probably be different in 5 or 10 years from what it is today. For example, in the case of collision incidents, risk for a given vessel depends not only on its own safety quality but also interaction with other vessels the density of which will clearly vary over time as well as changed in the legislative framework. The conventional rule of *"change in risk of collision is proportional to the square of change in traffic"* has been adopted here. However, there is uncertainty in this assumption and testing this relationship is left as a topic of future research.

Changes in the legislative framework might be difficult to anticipate but will influence safety standards for future vessel over and above what might be predicted by the incident models currently available. For example, although we may be able to forecast to what extent the composition of vessel fleet may be in a particular region based on anticipated changes in trade, those vessels may have somewhat different safety standards in the future and most likely increase in size. This is the reason we can only provide predictions of what risk may be in the future by applying our incident models to a given counterfactual traffic scenarios and assuming that all else is constant. This may be an area that can be further investigated as new risk factors might become relevant due to changes in the size of vessels and associated safety qualitities. Finally, forecasting future traffic is itself inherently uncertain.

Furthermore, uncertainties are associated with numerical models that describe the physical processes of how the combined forces of wind, waves and currents act upon the hull of drifting vessels or how oil spreads across water. Input data to model met ocean data present uncertainties in their own rights.

Uncertainty intervals for incident rates can be derived directly from historical incident data. Note that this is not the same as quantifying the uncertainty inherent in modelling the underlying system and does not directly address questions raised above. Historical data on maritime incidents are of poor quality, usually under-reported, and will contain substantial data errors. Indeed, global incident data used for this work was compiled from four different data sources (IMO, IHS Markit, LLIS and the Australian Maritime Safety Authority) which in itself reflect the challenges when basing assessments on the incident data directly.

A comprehensive uncertainty analysis that addresses all of the issues discussed in this section cannot be carried out at this stage. Information and data required to quantify the relevant uncertainties is not yet available. Computer simulations involving different components of the maritime system could (in principle) be carried out which would allow assessment of the uncertainty across the system including those individual components listed above.

4. Proof of concept – outcomes from a pilot project for strategic planning

4.1. Combination of data used

Table 1 provides an overview of the data used in the pilot project with AMSA. Vessel traffic data was used from terrestrial and satellite AIS systems (Automatic Identification System). Ship types which form the basis for the methodology developed are as follows: 1) general cargo, 2) dry bulk, 3) container ships, 4) tankers, 5) passenger vessels and 6) all other ship types. Fishing vessels and pleasure crafts were excluded.

The pilot contained Australia's Exclusive Economic Zone (EEZ) as well as results divided into three sub-regions – the North West Area (NW), the South West Area (SW) and the Great Barrier Reef area (GBR). A figure of the areas is provided in Appendix B along with the RouteNet or major shipping routes across the Australian EEZ.

The initial data which covers a large area had to be filtered to select observations within the Australian EEZ. Data errors had to be filtered out (refer to Appendix B for areas and AIS data errors). The project also used estimated world-wide nautical miles travelled and average days at sea from IMO (IMO, 2009) for calibration purposes of the yearly ship specific probabilities.

The logit models for ship specific probabilities are described in Appendix A along with the data sources of global incident data, global inspection data and ship particulars of the world commercial fleet. Around 500 variables were tested and evaluated in the logit model. Prior to using the data for the statistical models and for validation purposes, incident data was manually reclassified to match definitions of seriousness as by IMO (IMO, 2000) such as very serious, serious and less serious incidents and to identify first events of incidents. Missing data was complemented when possible to improve overall data quality. The ship specific incidents are then merged with AIS data using IMO or MMSI if IMO was not available.

Arrival forecasts at ship level and for the major shipping routes across the Australian EEZ came from AMSA and were projected by Braemer Seascope where preliminary figures were provided. For the integration of the met ocean conditions, a three year hindcast database of wind, waves and currents was provided by the CSRIO and vessel drift simulations of a dry bulk carrier were run by the Danish Hydraulic Institute of a pilot area – the Diamond Passage. The drift simulations provided the input data into this pilot project.

Table 1: Summary of data, data sources and time frames used

Data	Time frame	Use of data
Vessel positions *Source: 5-minute down-sampled AIS data from AMSA*	01/01/2014 to 31/12/2014, pre-formatted, cleaned data; linked with ship specific incident type probabilities	Risk estimation routine Calibration factors
Global incident data *Source: AMSA, IHS, IMO, LLIS*	01/01/2006 to 31/12/2010 19,740 observations, data compiled based on four sources	Logit models Model validation
Regional incident data *Source: AMSA*	02/01/1995 to 01/06/2013, 14,428 observations (pre-formatted, cleaned data)	Model validation
World fleet data at ship level *Source: IHS-Markit*	2006 to 2010 and 2012	Logit models Ship type classifications Calibration factors
Nautical miles travelled *Source: IMO, LLIS*	2007, 2013	Calibration factors
Drift simulations in the Diamond Reef Passage using 3 year hindcast data of wind, currents and waves *Source: DHI, BOM, CSIRO*	3 years	Hindcast data was used to run drift grounding simulations to derive 'time to shore'
Arrival forecasts *Source: AMSA based on a study from Bramer Seascope*	Number of arrivals by ship type for 2020 to 2025 for all major ports in Australia	Input data into the traffic density projections and associated risk exposure estimates

Note: AMSA = Australian Maritime Safety Authority, IHS = IHS Markit, IMO = International Maritime Organization, LLIS = Lloyds List Intelligence, DHI = Danish Hydraulic Institute, BOM = Australian Bureau of Meteorology, CSIRO = Commonwealth Scientific and Industrial Research Organization

4.2. Selected results for application at macro level

Based on the methodology described earlier and the data provided for the proof of concept, the following estimates for the baseline year 2014 and predictions for 2020 and 2025 are provided in Table 2. The effect for risk control options (RCO) is only provided for one sub area since the effects were taken from earlier work undertaken by DNV (2013) for this particular region. For validation, expected numbers of incidents are compared with actual observations when possible.

First we present results suitable for macro area such as the whole of the EEZ as well as larger sub-regions. The expected number of incidents is based on an increased traffic density forecast and ship specific risk without the spatial correction factor $RR_{sp}(s)$ of equation 3. We then present results for the integration of the metocean layer for drift groundings where the metocean layer is one example of a spatial correction factor to be used for more refined risk assessments at the micro level such as a particular passage or smaller area of interest.

Spatial visualization of estimates is important for policy makers in order to understand the magnitude and location of change of risk exposure for medium or long term planning aspects. This will allow the regulator to allocate resources for pollution responses but also choose and implement a set of risk control options to mitigate risk.

Based on the proposed methodology, the results for expected numbers of collisions is visualized spatially with flexible resolution in Figure 3 and compared with observed incidents. The expected numbers were calculated for each grid based on the safety quality of the ships that travelled in this area and the vessel traffic density which determined the ship specific risk exposure.

Table 2: Expected numbers of incidents by regions and year (base case year = 2014)

		Incident type (very serious and serious)			
Results by year		**Collisions**	**Powered groundings**	**Drift Groundings**	**Total**
North West (NW)	2011	0.50	0.64	0.97	2.10
	2014	0.70	0.74	1.10	2.55
	2020	1.04	0.91	1.39	3.34
	2025	1.04	0.92	1.41	3.37
South West (SW)	2011	0.37	0.35	0.56	1.28
	2014	0.42	0.34	0.51	1.28
	2020	0.82	0.53	0.91	2.26
	2025	0.86	0.55	0.95	2.37
Australian EEZ	2011	2.69	2.62	4.17	9.47
	2014	3.31	3.01	4.87	11.20
	2020	5.31	3.87	6.47	15.64
	2025	5.73	4.05	6.90	16.69
GBR (no RCO's)	2011	0.66	0.64	0.96	2.26
	2014	0.85	0.74	1.16	2.75
	2020	1.54	0.99	1.53	4.06
	2025	1.84	1.08	1.69	4.61
GBR (with RCO's)	2011	0.41	0.34	0.63	1.38
	2014	0.52	0.39	0.76	1.68
	2020	0.90	0.51	0.98	2.39
	2025	1.08	0.56	1.09	2.72
Observed (with all RCO's)		1.80	2.00	4.60	8.40
Expected (base case scenario)		3.31	3.01	4.87	11.20

Notes: calculations are restricted to AIS class 'A' vessels, EEZ = Exclusive Economic Zone of Australia, RCO = risk control options; unknown ship types were removed from calculations, observed incident data within the EEZ reflect any RCOs that were in operation during that period

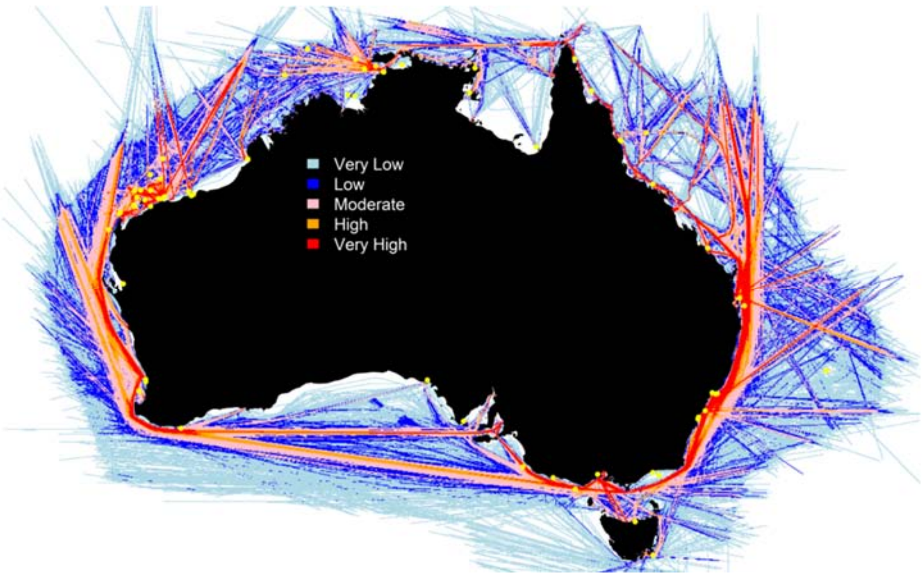

Figure 3: Observed collisions (any seriousness) during 1995 to June 2013 overlaid (as yellow circles) onto the risk assessment for collisions (VSS) in the Australian EEZ

The categories used in Figure 3 to classify the risk levels are very low to very high. The thresholds were based on providing a roughly equal number of grid areas for the '*moderate*', '*high*', and '*very high*' categories. All of the remaining grid areas defining the study area were then allocated to very low and low risk. The expected numbers of events appear very low as the associated area size (of a grid) is also very small (~3 nm^2). These maps provide an indication of hot spots across a large area such as the whole Australian EEZ since it provides the visualization of the risk areas in addition to calculated figures such as expected numbers of incidents.

Table 2 also presents a comparison of expected number of incidents to observed events recorded during a recent period (2006-2010) within the EEZ. These results were based on 38.3 million of nm travelled and risk profiles of almost 7,000 individual ships. It is worth noting that observed incidents were not accurate and were therefore treated with caution due to the quality issues associated with incident data mentioned earlier. Around 50% of the observations did not have coordinates (lat/long) and it was therefore difficult to associate them with an exact location. Despite these difficulties, it is nevertheless interesting to make informal comparisons against estimates based on historical incident data. These estimates indicate that the base case scenario is about 5% higher (for drift groundings) than what historical incident data might suggest and up to around 50-80% higher powered groundings and collisions.

Visualization helps to communicate how risk is spatially distributed and allocate resources such as risk control options to mitigate (e.g. Pilotage, VTS, navigational aids, traffic separations etc.). These types of Figures can also form the basis to simulate how risk exposure might change given a plausible set of traffic scenarios into the future with different maps for each traffic scenario. An example is provided in Figure 4 for the year 2020 and based on a *'business as usual'* economic development. Ideally, various scenarios reflecting different states of the economy (eg. bad economy, good economy, etc.) and associated ship arrivals can be applied in the future to see how these changes will affect risk exposure over time. The results can then be used as a basis for sensitivity analysis by running prediction scenarios with different combinations of risk control options. At this stage, a spatial correction factor is not yet applied for micro-level application.

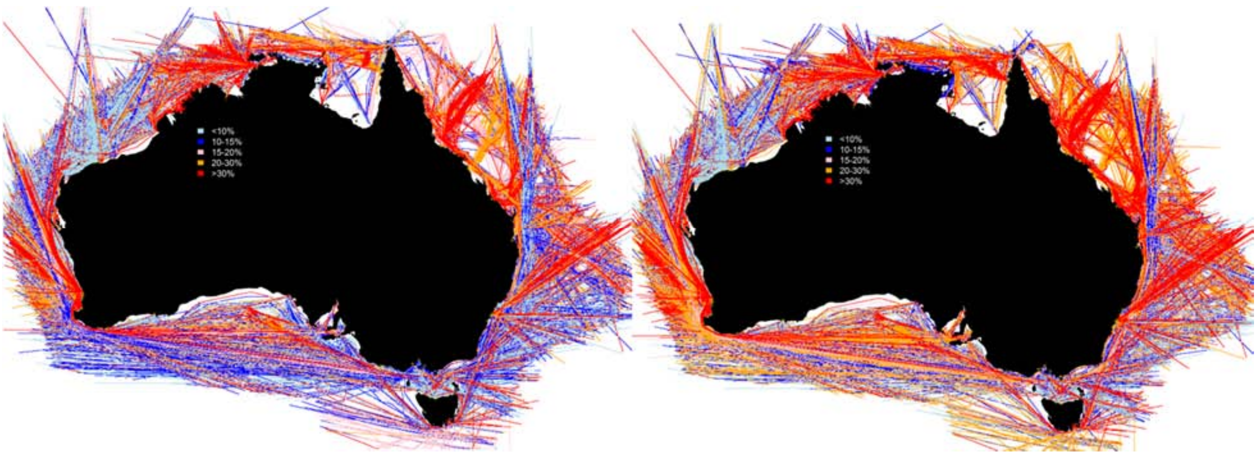

Figure 4: Change in risk exposure for powered groundings in 2020 (left) and 2025 (right) compared to baseline year (2014) across the Australian EEZ

4.3. Selected results for drift groundings

Drift groundings are of particular interest to AMSA since met ocean conditions on the Australian continental shelve can be complex and wind, waves and currents can come from different directions. Even though comparisons at the macro level for drift groundings leading to a very serious and serious incidents showed promising results (refer to Table 2), for drift groundings at a more refined level such as a passage or route, the relevant met ocean conditions need to be considered. In addition, areas close the outer reef of the GBR is far away from emergency tugs and it is often too deep to anchor in the case of an engine breakdown. For this reason, the risk of drift groundings is of particular interest at the macro and micro level where the integration of the met ocean layer summarizing the effect of wind, waves and currents on the probability of drift grounding was estimated using a 3 year hind cast dataset of met ocean conditions to derive the 'time to shore probability distribution' provided in equation 10 earlier.

The pilot area used for the simulation was the Diamond Reef passage and surrounding area where a small passage is used regulatory by vessels to transit through the area. Based on our approach, preliminary calculations provide an estimate for F_{drift} in 2014 within the Diamond Reef passage of 0.35 implying a return period of approximately 3 years. This estimate was calculated on the basis of combining ship specific probabilities for drift grounding candidates (proxy: main engine failures and steering gear failures) with traffic densities to produce a grid level estimate for F_{drift}. Note that a candidate estimate is irrespective of seriousness of the incident and a separate logit model was estimated compared to the macro level where only incidents leading to a very serious or serious incident were considered.

A distance density map for the Diamond Reef passage is presented in Figure 5 to illustrate the spatial distribution of traffic within this study area. Figure 5 also provides the probability density plot for the "time to shore "probability density function *(f_{TTS})* based on three years drift simulations by DHI of a bulk carrier using the relevant hind cast current and waves input data. Note that these calculations can be stratified by ship type (or possibly other ship level characteristics as required). For the purpose of illustrating the method, F_{drift} is estimated for a wider area around the Diamond Reef. Further research can enhance and validate the procedure for obtaining F_{drift}. and is currently underway using a more refined met ocean hind cast dataset of 6 years of data instead of 3 years and an improved drift simulation software by DHI to run drift simulations across larger areas.

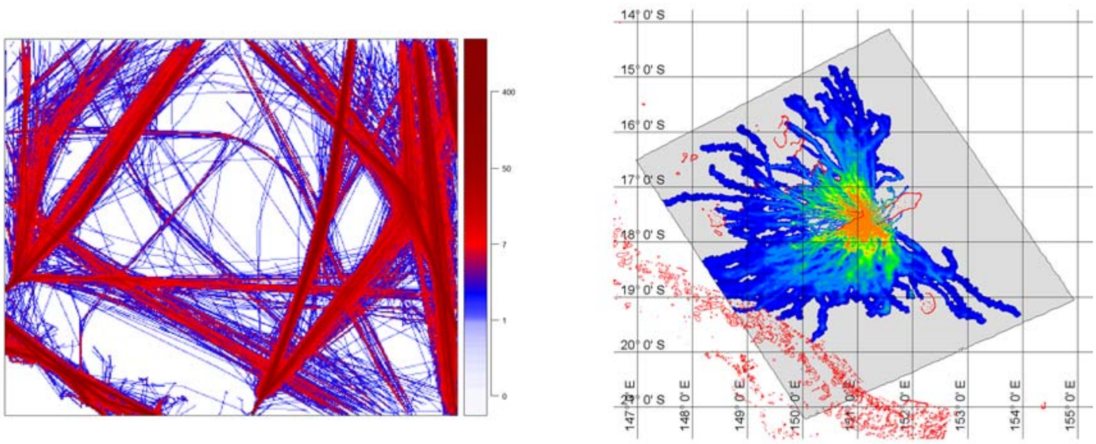

Figure 5: traffic density map (left) and time to shore density for the Diamond Reef Area

The preliminary drift grounding simulation for the Diamond Reef yielded a total number of 784 vessel groundings out of a total 1019 vessels released (p=0.77). Furthermore, assuming a fixed distribution for f_{TRT} of 24 hours, i.e. the nearest tug is located 24 hours from the Diamond Reef Area, we can also consider how many of these simulated drift events would be rescued by a tug. In this example, approximately 80% of the simulated drifting vessels result in grounding within 24 hours and therefore (further assuming zero probability of self-rescue) an estimate for $P_{grounding|drift}$ is calculated as 0.61. That is, under the assumptions highlighted, there is a slightly greater than 1 in 2 risk that a vessel grounds conditional on a drift event for the Diamond Reef passage. Expected frequency of drift groundings for the Diamond Reef for the simplified example is therefore equal to 0.2 (or a return period of 5 years).

To summarise, the approach for calculating $P_{grounding|drift}$ is illustrated here by counting the number of simulated drift candidates that result in grounding and estimating how many of these would have been able to either self-repair or receive assistance from tugs and ultimately avoid the grounding. In order to scale up the calculation, for a more comprehensive risk assessment, further consideration will be given to tug response time relative to the end lat/lon coordinate for vessels that ground. Similarly, a simple evaluation could also be applied to each simulated grounding and compare to expected self-repair time. The concept might also be further extended to consider the chance of anchoring, however, this may not be tractable given that anchor salvage will depend on bottom topography, bottom type (sand rock), and drift speed of vessel. At the moment, a separate pilot project will quantify 'available sea-room' by combining bathymetry with marine hazards and distance to baseline to provide an improved way to indicate whether a vessel has grounded or not by the simulation software.

Incorporation of all three modes of averting the grounding would need to be considered by studying the simulation output generated from the DHI model for each study area of interest. In principle, this approach for calculating $P_{grounding|drift}$ can be carried out for each grid area defining the study region. Initially, only data from the single point location could be used to illustrate the concept and further details around broader implementation would need to be advised.

It is envisaged that the process would be carried out in such a way so that the general calculations allow for a direct merge of expected numbers of drift candidates with risk of grounding conditional on drifting. In this way, risk of drift grounding can be assessed for a study region as a whole as well as spatially by combining the various layers of MLREF at the grid level.

A second approach can also need to be investigated further in order to better understand uncertainty around estimating drift grounding incidents. The idea would be to have a relatively simple method available to provide a best estimate of drift groundings as required and then a more detailed analysis that attempts to quantify underlying uncertainty when and if data on uncertainty become available. Monte Carlo techniques can be carried out by randomly drawing samples across all data inputs and by repeatedly running the simulation according to the uncertainty described by data and parameters. Uncertainty can be then propagated through the whole system.

Finally, the example presented here also illustrates a way of estimating the effect of an RCO. By running the calculations with and without adjustment for tug response, self-repair, or anchoring one can derive an estimate for an RCO (or set of RCOs). Again, the calculation is over-simplified here for illustration purposes and would likely be more relevant when scaled up to a larger area (for example the GBR region).

5. Conclusions and future research

The proposed multi-layered risk estimation framework provides a relatively straight forward approach to maritime risk assessment at the macro level with the possibility to downscale to the micro level by integrating a spatial correction factor. It can also be adopted for the strategic planning aspect and the operational aspect where the various layer can be combined to create an automated monitoring and alert system.

The major difference to other approaches is that we divide total risk exposure into layers which can be treated individually or in combined format. In such, the proposed approach allows the combination of the risk layers with flexible spatial resolution. One of its advantages is that it starts at the individual ship level in an attempt to quantify safety quality since risk is not homogenous across ships or areas. Combined with vessel traffic densities, this methodology can be implemented into traffic systems in either real time mode or used to estimate risk exposure expressed as various endpoints e.g. estimated number of incidents or in the future monetary value at risk based on Knapp and Heij (2016) which can be used as proxy to incident consequences and which allows improved cost benefit analysis and sensitivity analysis in evaluating risk control options.

Several extensions of this application include: 1) to improve estimation of risk at different spatial scales; 2) to assess risk over time; and to 3) predict risk in the future given risk control scenarios and finally 4) to use a combination of the risk layers to create an automated surveillance and alert system to enhance incident prevention.

We identified several areas of outstanding research to further improve our approach or complement it, especially for the micro level. To increase accuracy in areas where this is most relevant, a location specific calibration or weight factors should be developed and integrated into the routine as separate layer. This could be based on for instance historical candidates or it could be derived by a proxy variable that can describe traffic geometry such as for instance COG (course over ground), the average angle between passing ships or other proxies (Hansen, 2007). In essence, for collisions, this would be to find a proxy variable that can explain variation in traffic geometry without having to model the geometry in detail.

Furthermore, the current prediction routine still relies on the assumed relationship of the average number of collision encounters being proportional to the number of nm travelled squared (DNV 2013, Hansen 2007). With a projected increase in nm travelled, collision risk is therefore assumed to increase by a factor of 4. The temporal relationship between changes in traffic and risk exposure may be more complex and this assumption should be tested.

For strategic planning and in theory, risk can be calculated for each of the main shipping routes in the future or for areas of interest to a maritime administration. Most important layer extensions to the framework presented here are therefore associated with location specific risk parameters such as risk control options or underlying environmental conditions (wind, waves and currents). Another area of research would entail an improved routine to derive drift candidates besides using the logit model and in particular by integrating met-ocean conditions into the routine for drift candidates and using an improved vessel drift simulation software. A separate project is currently underway to investigate feasibility of this approach.

Another addition to the already existing layers which can serve all there risk exposure endpoints is the creation of an available sea-room layer which quantifies distance to a hazard at the horizontal and vertical level. Research in this area is currently on the way with another pilot project.

We also considered uncertainties and present various sources which would need to be considered if integrated into the general framework and more research is currently also dealing with this aspect. We aim to further assess all sources of uncertainty either stemming from input data or arising from simplifications and assumptions used in the modelling approach. One of the key next future steps will be to address how uncertainty is best handled here although, in reality, we recognise that a complete assessment of uncertainty will never be truly attainable.

The taxonomy of counterfactual exposure distributions is used frequently in other application areas (Murray CJL and Lopez AD, 1999) and would also be very useful within the context considered here to further assist with interpretation of results from maritime risk assessment. For example, theoretical minimum risk is the exposure distribution that would result in the lowest total risk, i.e. zero incidents, irrespective of whether currently attainable in practice. Plausible minimum risk refers to a distribution which is imaginable and feasible and is one that has been observed in particular sub-regions. Several other counterfactual distributions will be considered in the proposed framework here including the cost effective minimum risk in order to consider the cost of exposure reduction for a given set of RCOs. These definitions can be set according to the policy maker's perception of risk.

It is important to consider that risk assessment should allow for multiple approaches as each one will have its own strengths and limitations and will facilitate addressing different questions of interest of a maritime operation such as operational real-time monitoring of vessel traffic or medium or longer term strategic planning. Different approaches may be complementary, e.g. when a micro-level (mechanistic) model provides a better approach to quantify the effect of an intervention in a specific area while macro-level models allow real time applications for larger areas or strategic planning exercises.

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Appendix A: Logit models to estimate safety qualities of vessels

The underlying sample data is a combination of ship particular data of the commercial world fleet, historical inspection outcomes and past ship incident data for the period January 2006 to December 2010. Global incident information was combined from four different sources, and duplicates were eliminated. The remaining incidents were manually reclassified according to IMO definitions (IMO, 2000) for seriousness which are very serious (including total loss), serious, and less serious incidents. Besides manual reclassification per seriousness, incident initial events were identified when possible which forms the basis of the models. This allows a better distinction between incident initial events and consequences. The following model types were estimated:

Model type	**Use**
Collisions – very serious and serious	Macro level
Powered groundings – very serious and serious	Macro level
Drift groundings – very serious and serious	Macro level
Drift candidates – irrespective of seriousness	Micro level

The initial variables of all models and their respective groupings were selected based on Knapp (2006, 2011). The explanatory variables included in the models are the following:

- Ship type, age, and size (GRT) at the time of incident;
- Classification society, flag;
- Country where the vessel was built grouped into four groups as suggested by AMSA surveyors, and interaction effects with age groups (0-2 and above 14 years represent high age risk, while 3-14 years represent low age risk);
- DoC company and group beneficial owner country of location
- Number of deficiencies and incidents within 360 days prior to the incident;
- Changes of ship particulars overtime, such as flag changes, ownership changes, DoC company changes, class changes, and class withdrawals (within 3 years and within 5 years).

The base model used to estimate the models is the binary logistic model. Let x_i contain the explanatory factors such as age, size, flag, classification society, and owner, then the logit model postulates that $P(y_i = 1 | x_i) = F(x_i\beta)$, where the weights β consist of a vector of unknown parameters and F is a cumulative distribution function (CDF). A popular choice is the CDF of the logistic distribution, which gives the well-known logit model. This model states that

$$P(y_i = 1 | x_i) = \frac{e^{x_i\beta}}{1 + e^{x_i\beta}} \tag{1}$$

where $x_i\beta$ is a weighted average of all explanatory variables mentioned before. The probabilities are estimated at the individual ship level (i). The coefficients are estimated by quasi-maximum likelihood to allow for possible misspecification of the assumed logistic CDF.

Appendix B: Voyage database and AIS data processing

For the purpose of the pilot, one year of satellite and terrestrial AIS data and AMSA's RouteNet (Figure B1) was used to generate a voyage database. The purpose of establishing a voyage database is to facilitate generating a counterfactual traffic density based on an alternative scenario, e.g. traffic flow, pattern and vessel composition in the future (eg. 2020, 2025). The voyage database is then analysed to study aggregate level spatial features of traffic, e.g. regional level patterns (aggregated over the year), and also enable spatial risk assessment.

Each ship track in the voyage database is classified according to its ship type and voyage description, i.e. origin and destination along with additional summary information such as distance travelled; days at sea etc. A simpler approach to describing traffic flow along the RouteNet was also considered. At a very basic level, one could assume vessels follow routes as defined on the RouteNet. Implemented in this way, expected traffic volume and pattern under a counterfactual scenario can be extracted by simply applying the full set of port arrival forecasts to the RouteNet and proceeding with the risk assessment. However, in many ways, this would be inadequate as the simplification of reducing traffic movement to a one-dimensional (linear) model, even at an aggregate level, would ignore the fuller spatial aspects of traffic (and risk) which will likely be needed to address particular risk related questions that arise later.

One such area of interest concerns testing whether abnormal vessel behaviour might be assisted with the establishing of a database containing 'normative' ship tracks. Furthermore, whilst to a large extent, vessels often do follow a prescribed single path from point of origin to destination, understanding where and when this does not occur should be a part of any maritime risk assessment.

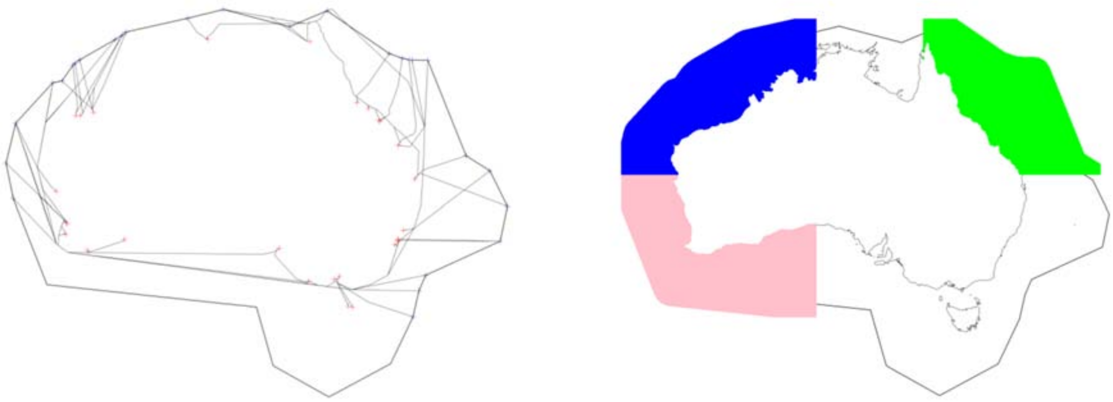

Figure B1: AMSA' RouteNet and sub-regions (blue=NW, pink = SW and green = GBR)

The voyage database consists of a collection of spatial lines representing the full set of voyages departing/ending in each major port defined on the RouteNet. The corresponding position on the EEZ boundary is also tagged for each voyage that leaves the EEZ region.

Let $\mathbf{SL}_{ij}$ represent the spatial line that summarises the complete set of movements for voyage **j** of ship type **i.** For every voyage $\mathbf{SL}_{ij}$ a record is also created and added to other summary level data to be used as an index to the actual ship track database **SL**.

For each $\mathbf{SL}_{ij}$ the corresponding distance travelled $\mathbf{d}_{ij}$ together with other high level summary data is recorded on the index dataset. For the analyses carried out, each voyage was further disaggregated according to the portion corresponding to activity within a port area. Although this disaggregation was not required for the current project, several exploratory analyses have been carried out to study aggregate level vessel behaviour at the port level, e.g. port level traffic density and inter-arrival times.

The voyage database also captures other detail that may be of interest including whether the vessel enters the EEZ region and bypassing major ports. Preliminary findings indicate that this comprises a relatively small proportion of total traffic, however, it is still required for the purpose of the risk assessment.

Each ship track recorded in the voyage database is classified according to the following five categories:

1) **port2ee:** ship track from port to entry/exit (ee) wayward point on the EEZ boundary
2) **ee2port:** ship track from ee to port
3) **port2port:** ship track from port to port
4) **port:** ship track within port
5) **ee2ee:** ship track from ee to ee, i.e. voyage not tagged as arriving at a port defined on the RouteNet

where:

- *vessels can depart and arrive back into the same port in which case they are classified under category #3.*
- *travel for some vessels is restricted exclusively to within the port area. In practice, this did happen with a relatively small proportion of the vessels included in sample data provided by AMSA.*
- *a port arrival was defined as a vessel staying for at least 12 hours within a 36 nautical radius of a major port.*
- *passing through an* ***entry/exit (ee)*** *point was defined as an intersection of a ship track anywhere along the EEZ regional boundary. Note that* ***ee*** *intersections were tagged against major* ***ee*** *positions if the vessel crossed within 90 nautical miles and were otherwise tagged as* ***ZZ****.*

The definition of a journey passing through an entry/exit point (ee) on the RouteNet is somewhat arbitrary. Different distance values were considered and the numbers of voyages appeared to stay reasonably stable for most routes. A number of journeys could not be associated with a route as defined on the RouteNet such as voyages travelling across the EEZ regional boundary but not through waypoint defined on the RouteNet. Again, this does not directly affect risk calculations.

Several algorithms were tested to clean the ship track data and remove anomalies due to problematic AIS data as follows:

- When a gap between successive AIS readings was less than 24 hours during which time the effective speed was greater than 75 knots. An error is identified whereby the calculated effective speed in invalid.
- When a gap between successive AIS readings was greater than 48 hours and 500 nautical miles distance. This occurred mostly outside the EEZ region. Tracing of ship track data is reset for a given voyage to avoid introducing potential errors.
- Single anomalies with invalid lat/lon are identified and removed, e.g. the vessel suddenly jumps to an invalid coordinate but then immediately returns to the original tracking position. Other cases involving the AIS data show inconsistencies throughout most of the ship track data whereby it is unclear which route the vessel is on as the positions repeatedly change back and forth between two very different locations.

Designing an optimal set of routines for handling AIS data was beyond the scope of this project. Specifically, tracks considered to be invalid were removed prior to analysis. The total amount of data removed by employing this step was equivalent to removal of approximately 6M nms.