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NowIce – predicting transit times of ships in winter navigation

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FOREWORD

In this report no 106, the Winter Navigation Research Board presents the report describing the NowIce study. The study aims at finding out the possibilities for a new tool for the icebreakers, merchant vessels and logistics operators to estimate the severity of the ice situation.

NowIce study has two main objectives: the first objective is to determine to what extent observed slow-downs (due to ice conditions) of ships in a limited sea area during the past 24 hours can be used to predict the slow-downs of other ships in the same area. The second objective is based on AIS data from several winters which is prosessed and analysed to obtain quantitative estimates on the correlation of slow-downs between different ships moving in the same ice covered areas.

The results of the study indicate that there are possibilities to use the past tracks of the ships to predict the speed and route that the ships are going to take.

The Winter Navigation Research Board warmly thanks Mr. Robin Berglund, Mr. Lauri Seitsonen and Mr. Jorma Kilpi for this report.

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May 2020

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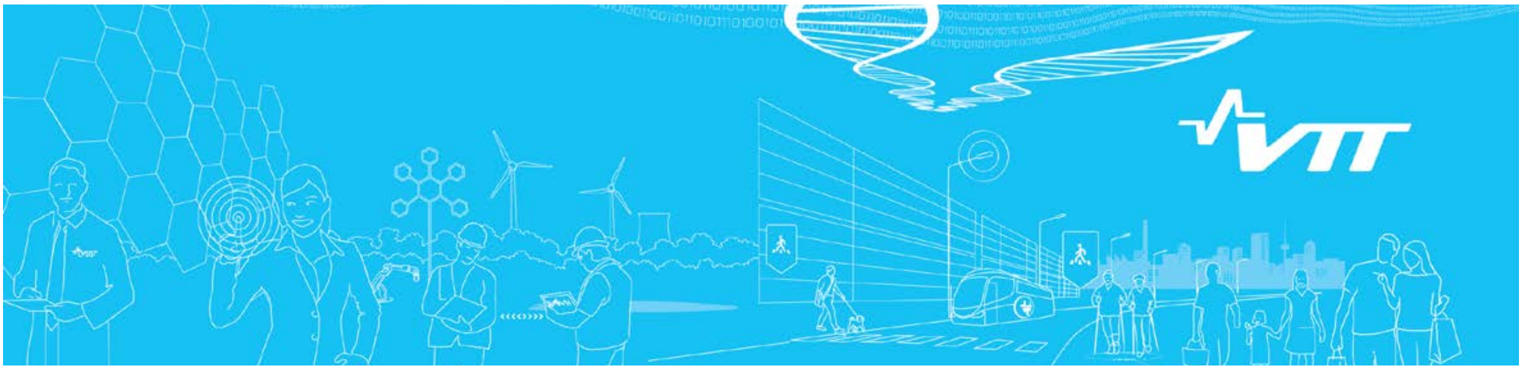
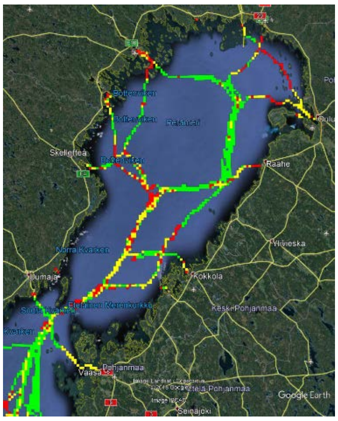


RESEARCH REPORT

VTT-R-02863-18
16th August 2018



NowIce - predicting transit times of ships in winter navigation

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Summary

This report describes the work and results obtained in the NowIce study, which aims at finding out the possibilities for a new tool for the icebreakers, merchant vessels and logistics operators to estimate the severity of the ice situation with the help of observed ship speed information. These estimates would enable more accurate scheduling of ship loading/unloading operations, improve route planning and reduce fuel consumption as well as emissions, if the effects of the ice conditions along the planned route could be predicted more accurately.

NowIce has two main objectives: the first objective is to determine to what extent observed slow-downs (due to ice conditions) of ships in a limited sea area during the past 24 hours can be used to predict the slow-downs of other ships in the same area. The second objective is to determine the usability of ice forecasts for predicting slow-downs of ship. The analysis is based on AIS data from several winters. The data is processed and analysed to obtain quantitative estimates on the correlation of slow-downs between different ships moving in the same ice covered areas.

The results indicate that there are possibilities to use the past tracks of ships to predict the speed and the route that the ships are going to take, but the uncertainties are rather large. Utilising machine learning techniques, the numerical ice forecasts can be utilised to predict the speed of the ships in ice. However, predicting the waiting time for ships beset in ice requires other approaches, which has to be taken into account when evaluating the usefulness of the algorithms presented here.

The study has been performed by VTT and funded by the Research Board for Winter Navigation.

Confidentiality	Restricted

Espoo 17.8.2018

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Preface

This study, funded by the Winter Navigation Research Board aims at finding the possibilities for a new tool for the icebreakers, merchant vessels and logistics operators to estimate the severity of the ice situation with the help of observed ship speed information and ice forecasts. If the effects of the ice conditions along the planned route could be predicted more accurately, these estimates would enable more accurate scheduling of ship loading/unloading operations, improve route planning and reduce fuel consumption as well as emissions.

NowIce has two main objectives: the first objective is to determine to what extent observed slow-downs (due to ice conditions) of ships in a limited sea area during the past 24 hours can be used to estimate the slowdowns of other ships in the same area. The second objective is to determine the usability of ice forecasts for predicting slowdowns of ship. The analysis is based on AIS data from several winters. The data is processed and analysed to obtain quantitative estimates on the correlation of slow-downs between different ships moving in the same ice covered areas.

The study, performed from January to June 2018, was organized into 4 tasks:
Task 1. Detailed research plan
Task 2. Data preparation and preprocessing (AIS and ice forecasts)
Task 3. Data analysis
Task 4. Reporting and presentation of results

The work was supervised by a Steering group consisting of the following members:
Markus Karjalainen, Finnish Transport Agency
Lauri Kuuliala, Finnish Transport Safety Agency
Jorma Kämäräinen, Finnish Transport Safety Agency
Amund Lindberg, Swedish Maritime Administration
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The Steering Group convened 2 times.

Espoo 29.6.2018

Authors

Contents

1. Introduction

The effect of ice on ships is a relevant topic as it affects logistics planning, ship design and how to mitigate the adverse effects of a seasonal ice cover on shipping. Data obtained from the AIS system, which is compulsory for all relevant categories of merchant ships, enables systematic analysis of data obtained during several seasons and all kind of ships that participate in the transportation chain. From a logistics planning view, having an accurate prediction of the voyage time for individual ships, is valuable.

An approach that has been piloted in previous studies and also implemented as a service to ships, is to analyse the speed of the ships during a time frame of a day or so, and use this information to predict the slowdown of ships entering the same areas. The idea is analogous to road traffic information maps - with the distinction that ships do have much more varying speed - even in open water conditions - and there are no fixed road networks (except when ship traffic is limited to predefined channels). Furthermore, ships can be beset for a time period the length of which mainly depends on the vicinity of the icebreakers and their assistance duties and not directly of the ice conditions.

Another way of estimating slowdown of ships is to use ice condition information and relate this to the performance of ships. This can be done either from an engineering point-of-view - using ship design models, or by observing the performance of ships when in ice and building a model out of this data. An interesting question is which approach will give a better prediction of the travel time for ships in wintertime.

In this report, the terms *prediction* and *estimation* are used almost interchangeably, although we have tried to use the term *prediction* in the cases where we forecast future values and *estimation* for the estimation of values without the time component involved.

The study can become a foundation for a new tool for the icebreakers, merchant vessels and logistics operators to predict the severity of the ice situation with the help of observed ship speed information. If the effects of the ice conditions along the planned route could be predicted more accurately these predictions would enable more accurate scheduling of ship loading/unloading operations, improve route planning and reduce fuel consumption as well as emissions.

1.1 Summary of previous studies

There are two aspects in ice performance considerations of ships: ice load on the ship hull and ice resistance. In ship design, the ship hull should be strong enough to prevent excessive damage during the planned lifetime of the ship in the areas of planned operations. A damage to the ship hull may lead to an oil spill or have other catastrophic consequences. Ice resistance should be accounted for to enable the ship to manoeuvre and maintain sufficient speed in the intended areas with the expected ice conditions.

When operating in ice conditions, it is important to be able to estimate ship speed and need for assistance when knowing the ice conditions. An improved prediction of arrival times to ports and travel times through the ice covered fields would enable more efficient logistics planning. Long term predictions of travel times and the need for icebreaker assistance capacity are important when planning investments in specially built icebreakers.

The traditional approach to estimate ice resistance is by using analytical and numeric modelling. The models are then verified using model scale tests and full scale campaigns. The difficulty here is that the ice resistance models are valid only for certain homogeneous ice conditions like level ice and uniform channel rubble. These “pure” conditions are, however, seldom encountered in practice. Another problem is that the models require exact knowledge of several ship hull parameters (bow angles etc.), which makes them difficult to apply for a wider set of vessels. Ice conditions are also difficult to monitor (and forecast) with the accuracy required for the models to be usable.

The 2002 IMO SOLAS Agreement included a mandate that required most vessels over 300GT on international voyages to carry a Class A type AIS transceiver. Thus AIS transceivers are compulsory on practically all vessels that are interesting from a winter navigation point-of-view. Several organisations (also VTT) have archived this data originating from the AIS terrestrial base station network and this now makes a statistical approach to the problem feasible.

In the IceTrafprep-study (Berglund et al, 2012) the concept of using AIS data and compare the speed of the ships with their (normal) open water speed, was elaborated with the focus on how this methodology could be used as the basis for a new service to indicate the ice conditions at sea. The study concluded that the slowdown of ships indeed correlate with the severity of the ice conditions and can be used as an indicator. However, no quantitative analysis was done in this study but this was followed up with a feasibility study (ISABELIA) funded by the European Space Agency.

In the paper by Kotovirta et al (2011), the idea of using observed ship speed (or slow-down) as a proxy for ice thickness, was elaborated. The conclusion was, however, that there is a quite large RMS error of the model even though special conditions (like icebreaker assistance and proximity to ports) were excluded from the study.

Löptien et al studied the correlation between ice conditions and ship speed information in their paper (2014). Their conclusion was that 62 - 67% of ship speed variations can be explained by the forecasted ice properties when fitting a mixed effect model where the speed dependency on ice concentration, ice thickness and degree of ridging is expressed as a sum of a general dependency and ship wise linear relationship.

Lensu et al has made a comprehensive study (2017) comparing IAS iceclassed ship performance and ice information (derived from ice charts). In the study the following differentiation was made between different averages that can be calculated from the speed observations of ships:

- message average - average speed of all vessels calculated from the AIS messages per ice thickness class
- ship average, - average speed for each vessel calculated per ice thickness class
- fleet average, - average speed for a fleet of vessels per ice thickness class
- climatological average - average of speed of vessels per gridcell and class of average ice thickness
- grid average - average of average speed per gridcell per ice thickness class

In the analysis in the current study, the AIS position reports are harmonised to represent the estimated (interpolated) position of all ships at 5 minute intervals. This simplifies the calculation of relative distances and removes biases due to varying message intervals. Otherwise the averages are calculated as ship averages per gridcell.

2. Goal

2.1 Research questions:

Question	Why	How
Is it possible to predict slowdown of ships by monitoring slowdown of other ships that have transited the same route during the past 1 - 24 hours?	To get a quantitative measure of the prediction accuracy of an algorithm that is based on a simple nowcasting model	Using the framework implemented operationally for predicting ETA:s - perform a systematic comparison of predictions vs realized travel times. The predictions are based on average slowdowns of the ships. This is done for the 2013 winter situation to start with. The result shows statistics for the prediction accuracy
Can we improve the prediction accuracy by using numerical ice condition models?	To get a quantitative measure of the prediction accuracy of an algorithm that is based on numerical models of the ice (in the Baltic Sea)	We will build a model that is using ice condition data and information of proximity to other ships, then evaluate the accuracy that this model achieves. The main steps are: 1) preprocess AIS data a. producing snapshots with 5 minute intervals 2) align the AIS data with reanalyzed ice data in a 3-D matrix (lat, long, time)- grid 3) train a mathematical model 4) compare model results with actual outcome

3. Methodology

The study is based on AIS data and on ice conditions obtained from reanalysis of ice model data.

The first question is approached as shown in Figure 1, the second one as in Figure 2.

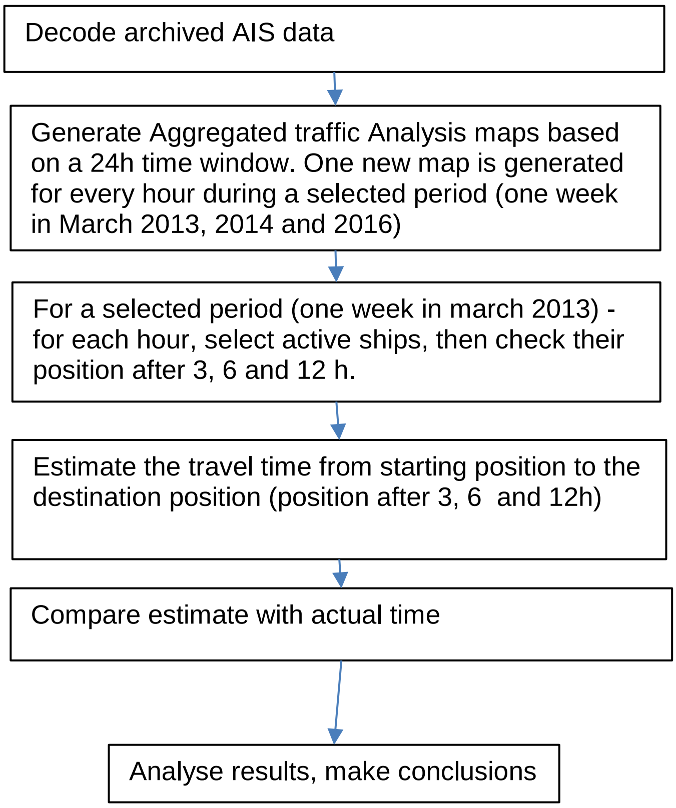


Figure 1 Analyse track-based travel time estimate accuracy

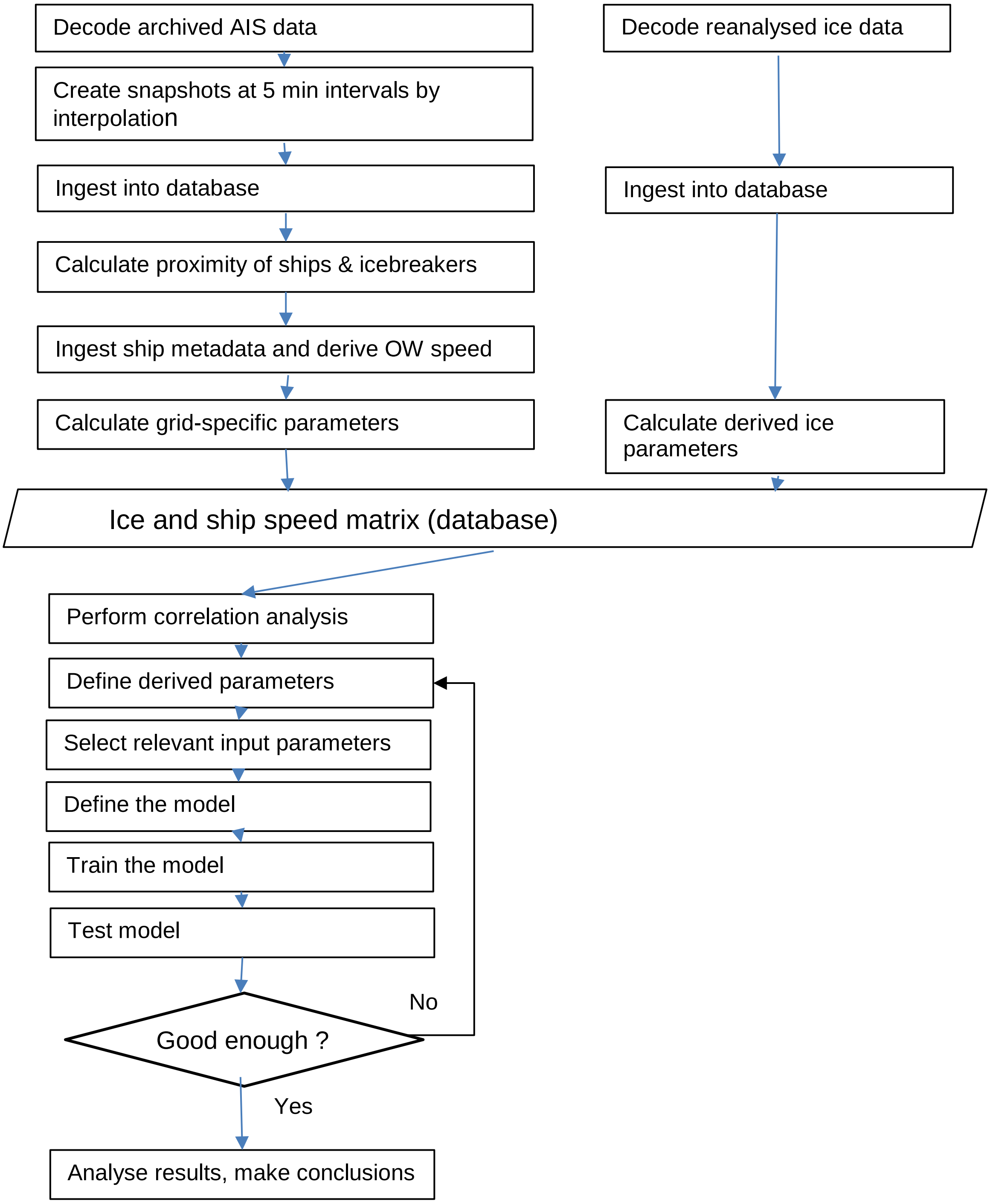


Figure 2 Analyse ice condition based predictions

The added value of this study compared to earlier ones is as follows:

1) to obtain quantitative accuracy estimates of the predictions calculated according to the algorithm in Figure 1, and

2) for the second case that the model includes both ice information and information about other ships in the vicinity and the time (difference) since the cell has been visited by another ship on a similar course (or counter course). This will (hopefully) capture the effect of ships steaming in channels or being assisted by an icebreaker.

In the second case the comparison is done for all ships moving in the Bay of Bothnia, for each time slice (5 minutes) calculating the predicted speed value given ice conditions, ship parameters and time since previous ship passage. The predicted speed is compared to observed speed value and suitable metrics is applied (RMS error of the relative speed being the most important indication).

The study will not try to evaluate the accuracy of Estimated Time of Arrival or travel times based on ice condition information, as the travel times are very much depending on the interaction between icebreakers and ships. Further studies could be based on simulations where assistance rules would be applied in combination with ice condition modelling and ship traffic simulation.

3.1 Data used in the study

3.1.1 Ice conditions

The periods that are used in the study are from three winters: 16 - 23.3.2013, 5 - 12.2.2014 and 16 - 23.3.2016. These periods are selected on the basis of having enough ice conditions in the material, but also representing typical ice winters during the last 5 years. The week in 2013 has also been used in previous studies - enabling comparison with previous results if considered meaningful.

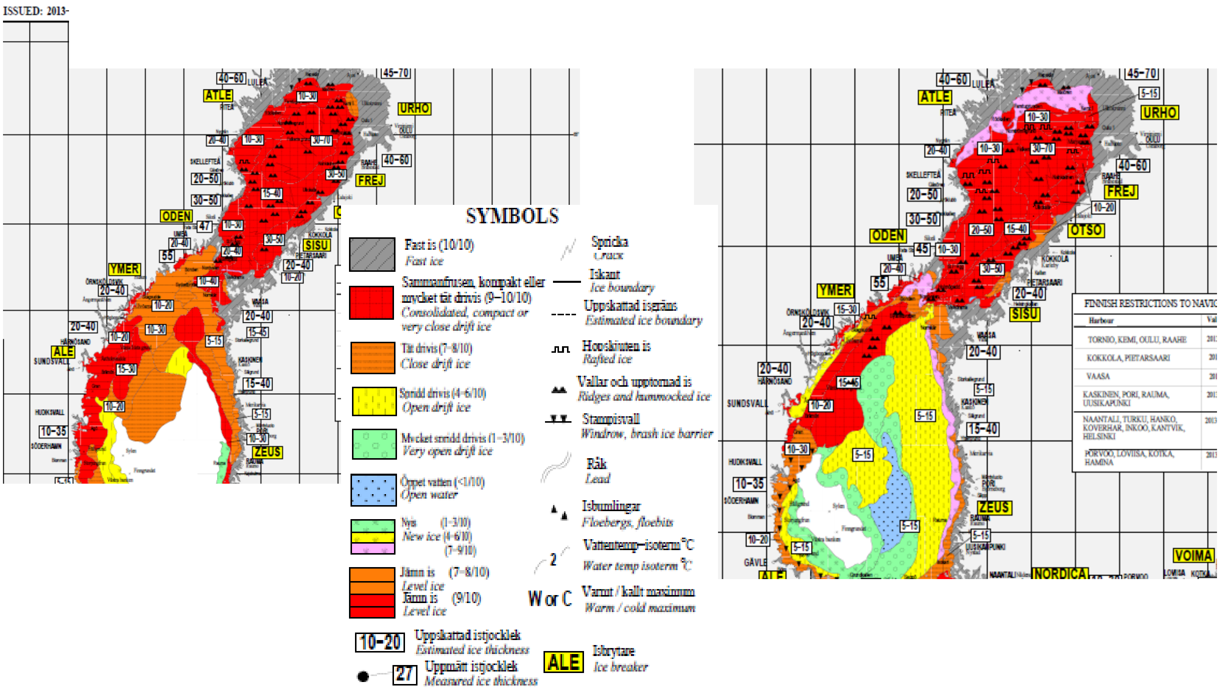


Figure 3 Ice conditions 16.3 and 23.3.2013. Ice chart by SMHI

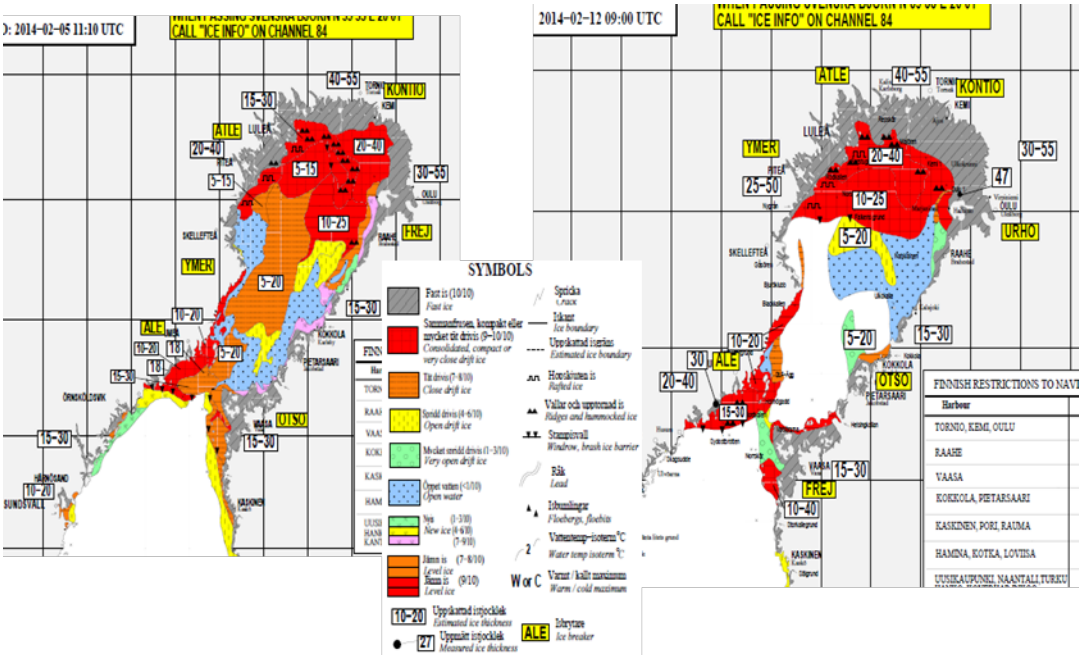


Figure 4 Ice conditions 5.2 and 12.2.2014. Ice chart by SMHI

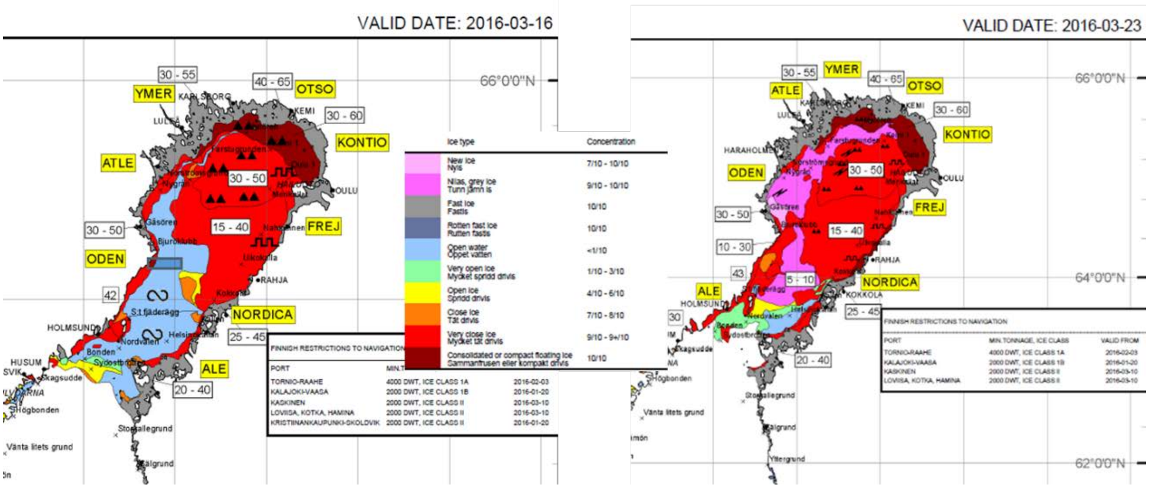


Figure 5 Ice conditions 16.3 and 23.3.2016. Ice chart by SMHI

3.1.1.1 Closer look at the ice conditions 16 - 23. 3.3013

During the week 16 - 23.3.2013 there was a change in wind direction on the 19-20.3. This caused ice compression north of the Quark and ships had to wait for icebreaker assistance to proceed.

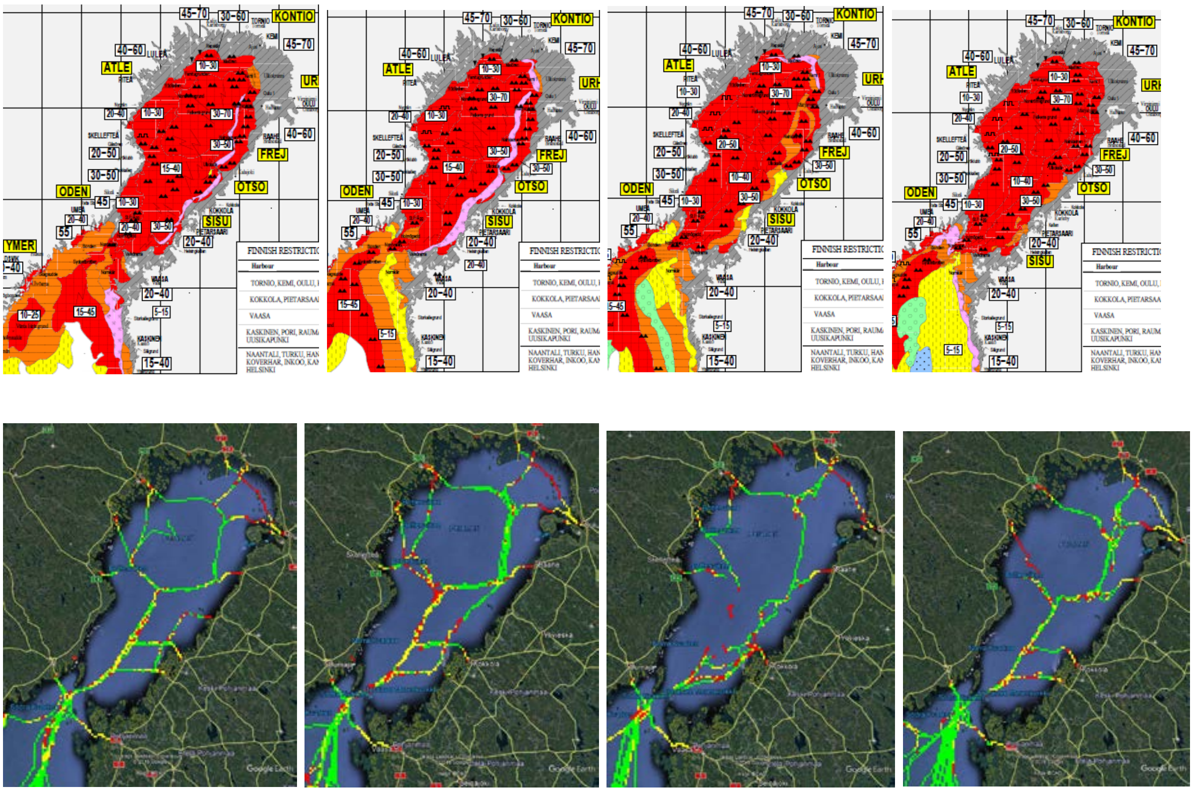


Figure 6 Upper row: Ice conditions 19, 20, 21 and 22.3.2013. Ice drift is visible in the ice charts (changes seen when comparing icecharts from subsequent days). Icechart by SMHI. Lower row: Ice trafficability charts where the relative speed of the ships is calculated and visualized as an aggregate of the ship movements in each gridcell for 24h up to 10 UTC the given day. On the 20th there are clear indications of slow-downs of the ships North of the Quark. On the 21st there are still a few ships that are stuck in the southern part of the Bay of Bothnia. The next day (the 22nd) the situation has improved with some problems in the middle of the Bay of Bothnia.

3.1.2 Ice data

The numerical gridded data used in the study are from the Finnish Meteorological Institute. The data is produced by a numerical model of the ice conditions as a result of a reanalysis process where observations have been assimilated in the model to produce the best estimate of the ice conditions expressed in a lat/long matrix with 1 nautical mile grid size and a temporal resolution of 1 hour. The parameters in the model are listed in Table 1.

Table 1 Parameters of the numerical ice model

Parameter	Description
hi1 - hi5	5 level ice thickness categories averaged over the gridcell. The real thickness of an ice floe in category 1 is thus hi1/a1
a1 - a5	concentration of the 5 level ice categories
hsnow1 - hsnow5	Snow thickness categories
ui, vi	Ice drift velocity components (eastwards, northwards)
hri	ridged ice thickness averaged over the gridcell. Average ridged ice thickness: hri/ari
ari	Concentration of ridged ice. (0.0 - 1.0)
hra	rafted ice thickness averaged over the gridcell. Average rafted ice thickness: hra/ara
ara	Concentration of rafted ice. (0.0 - 1.0)
dsigdx, dsigdy	Stress, x and y- derivatives

3.1.3 AIS data

The AIS data used in the study originates from the terrestrial base station network in Finland and Sweden which has been archived at VTT. The parameters used in this study are MMSI number, Speed over ground, Longitude, Latitude, Course over ground. In addition the following ship metadata information is extracted: ship type, ship length, Ship breadth.

Only AIS data with navigational status *Under way using engine* (0), *Constrained by her draught* (4) or *Undefined* (15) was used in the study. Data from detected harbour areas was excluded as well. The harbour detection was based on the statistics, i.e. areas where navigational status *Moored* (5) was commonly used or areas where the vessel speed was typically exactly zero. The sampling process first detects continuous AIS tracks. The track is split if there is an over 30 minute gap between two consecutive AIS messages and the average speed between the points is less than 3 knots (indicating anomalies in the voyage in which case a linear interpolation probably would lead to erroneous results). If the gap between the messages is over 4 hours, the track is always split. Data rows that would result in a segment speed over 100km/h were ignored. Further pre-processing differs between the track-based and ice data based approaches.

In the **track-based approach** the AIS data is resampled spatially at intervals matching the grid size in projected coordinates. If the vessel has not moved to cover the grid size in 30 minutes, a new point is interpolated so that the maximum distance of the interpolated points is either the grid size or 30 minutes if the points are closer. The data for the analysis is further constrained by excluding icebreakers from the data.

In the **ice data based approach** the AIS data is resampled to 5 minute intervals. The track is then resampled to sharp 5 minutes by following the track and positioning the resampled point using linear interpolation. The average speed of the split track part is used as the speed for the resampled observation. The data for the analysis is further constrained by excluding icebreakers from the data, as well as those vessels for which we did not have ice class or reference speed information available. Vessels with AIS ship type 1 - 39 (fishing, towing, dredging, diving, etc.) or 50 - 59 (special crafts, including pilot vessels) were excluded in the study. (See ITU-R M.1371-5, Annex 8, Table 53 for coding of *Type of ship* in the AIS system)

3.1.4 Ship metadata

Additional data about ships is obtained from a ship register used by the icebreaker system IBNet. The most important parameters are: Iceclass, machine power (maximum) and DWT. Also the nominal speed in this register is used as the reference value (open water speed value).

4. Limitations

The study only uses a limited set of data: one week in 2013, 2014 and 2016. A comparison of the methods is limited to comparing the accuracy of the speed estimates. On the machine learning side, only a limited set of parameter combinations have been tried out, and no simulation trials have been done to predict ETA times in cases where ships are beset and proceeding only with the assistance of icebreakers or other ships. The area covered is within a bounding box of 17.15 to 25.4 Eastern longitude and 60.5 to 65.75 Northern latitude.

When evaluating the accuracy based on observed ship voyages, only voyages that have passed through gridcells that have been visited during the last 24 h, are possible to evaluate.

5. Methods

5.1 Prediction of voyage times

To predict the voyage time T from position A to B, both the speed and the distance to be travelled, have to be estimated. In the track-based gridcell approach that we have used, this is done as follows:

$$T = \Sigma\, t_i \text{ where } t_i = L_i / v_i \qquad (1)$$

$$L_i = d \text{ or } \sqrt{2} * d, \text{ (depending on direction of gridcell step)} \qquad (2)$$

d = gridcell width (same as gridcell height, square cells)

$$v_i = v_{OW} * r_i, \qquad (3)$$

v_{OW} = open water speed of ship,

r_i = average of relative ship speed per grid cell, $r_i > 0$.

The track estimation and the speed estimation will be examined separately. To start with, we have evaluated the total travel time estimate using the actual voyage of the ships. The results are shown in Figure 7 and Figure 8 where actual 3h routes of ships have been used, but the estimated speed in each grid point is determined from grid cells of different sizes. The estimate is further divided into days, depending on the start time of the voyage.

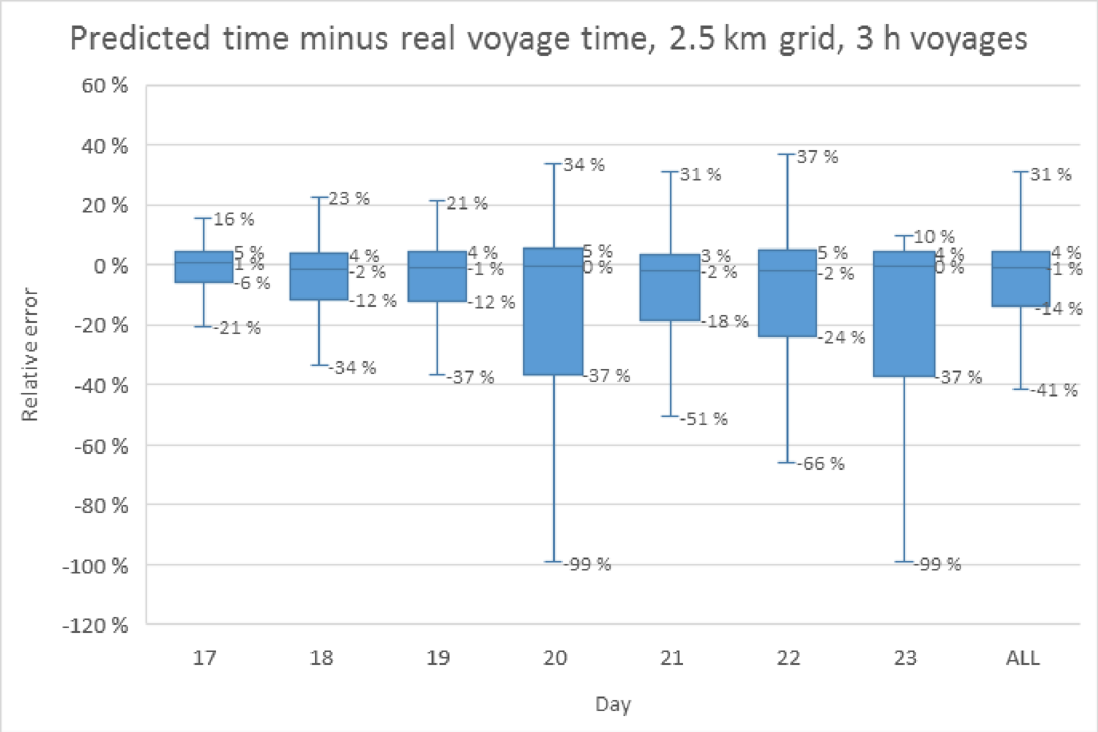


Figure 7 Predicted travel time minus observed travel time for voyages of 3 h duration. Speed estimated from a 2.5 km grid. The result is shown in a Box-and Whiskers diagram leaving out outliers. The line in the box shows the Median, the box shows the lower and upper Quartiles (Q1 and Q3) and the whiskers show the highest (lowest) value less than (higher than) a value calculated as the upper (lower) quartile plus (minus) 1.5 x IQD. IQD (InterQuartile Distance) is calculated as Q3 - Q1.

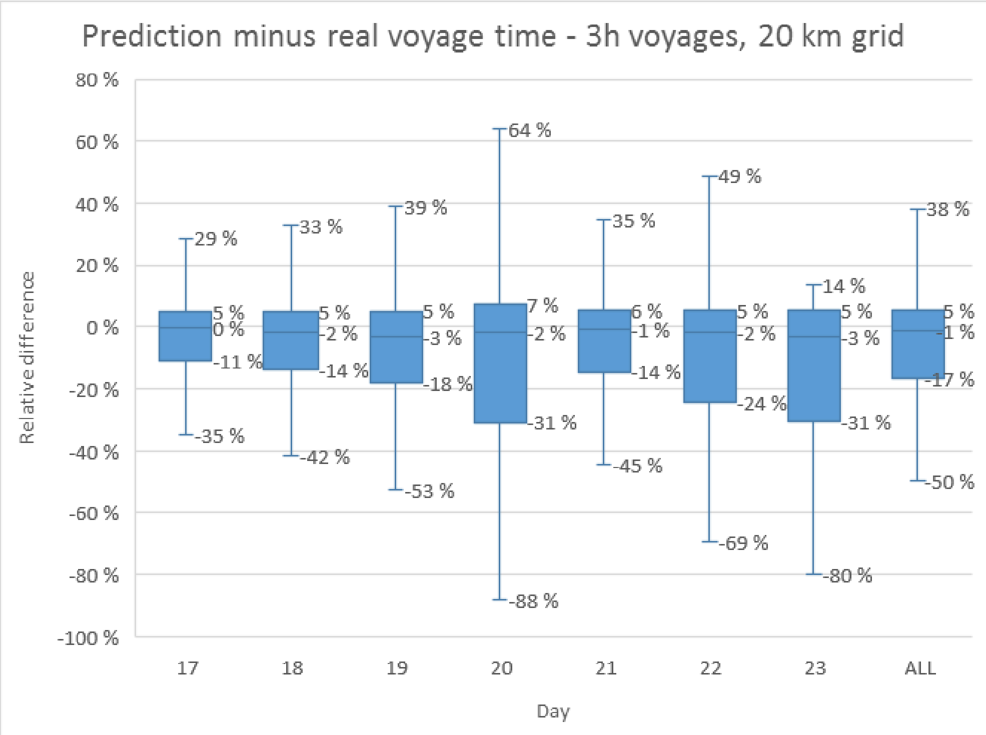
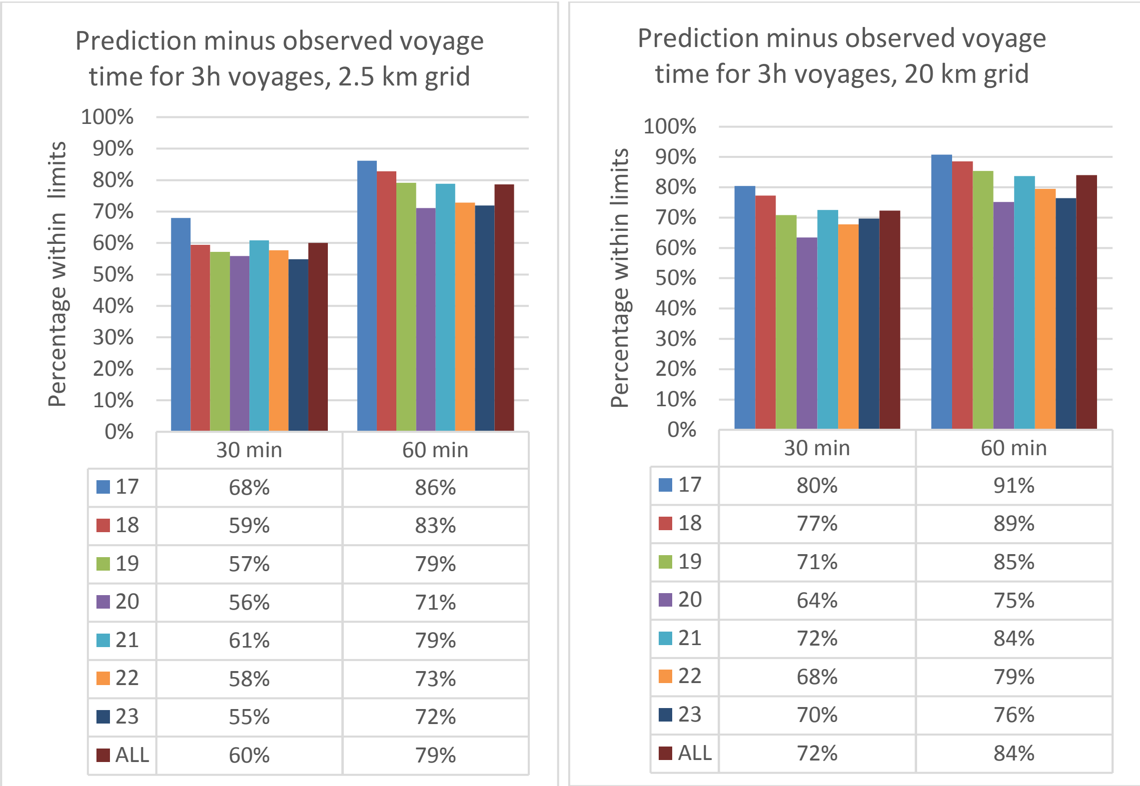


Figure 8 Predicted travel time minus observed travel time for voyages of 3 h duration. Speed estimated from a 20 km grid.

Another way of expressing the accuracy is to count how many of the predictions were within predetermined time limits. We have here used the time limits 30, 60 and 120 minutes in the figures below.



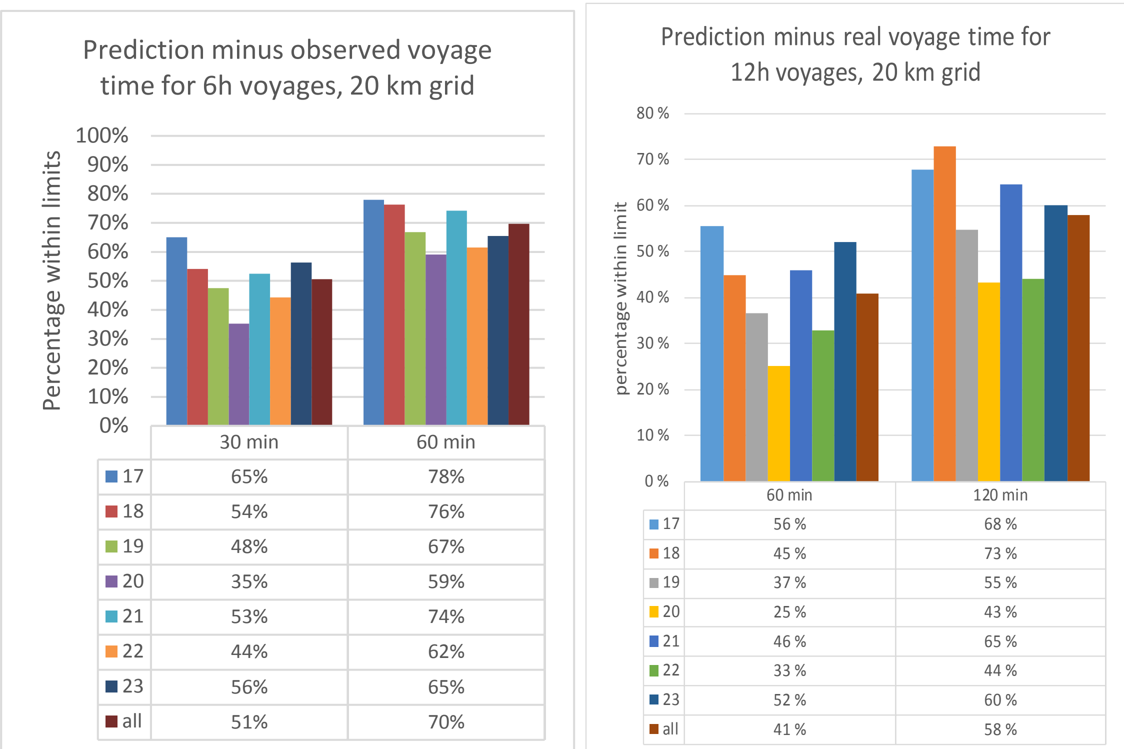
3h voyages, 2.5 km grid

	30 min	60 min
17	68%	86%
18	59%	83%
19	57%	79%
20	56%	71%
21	61%	79%
22	58%	73%
23	55%	72%
ALL	60%	79%

3h voyages, 20 km grid

	30 min	60 min
17	80%	91%
18	77%	89%
19	71%	85%
20	64%	75%
21	72%	84%
22	68%	79%
23	70%	76%
ALL	72%	84%

Figure 9 Predicted travel time minus observed travel time for voyages of 3 h duration. Measured as percentage within +-30 and +-60 minutes of a 3 hour voyage. The numbers (and bars) represent different days of the month and "all" means the overall result for all days (17 - 23.3).



6h voyages, 20 km grid

	30 min	60 min
17	65%	78%
18	54%	76%
19	48%	67%
20	35%	59%
21	53%	74%
22	44%	62%
23	56%	65%
all	51%	70%

12h voyages, 20 km grid

	60 min	120 min
17	56 %	68 %
18	45 %	73 %
19	37 %	55 %
20	25 %	43 %
21	46 %	65 %
22	33 %	44 %
23	52 %	60 %
all	41 %	58 %

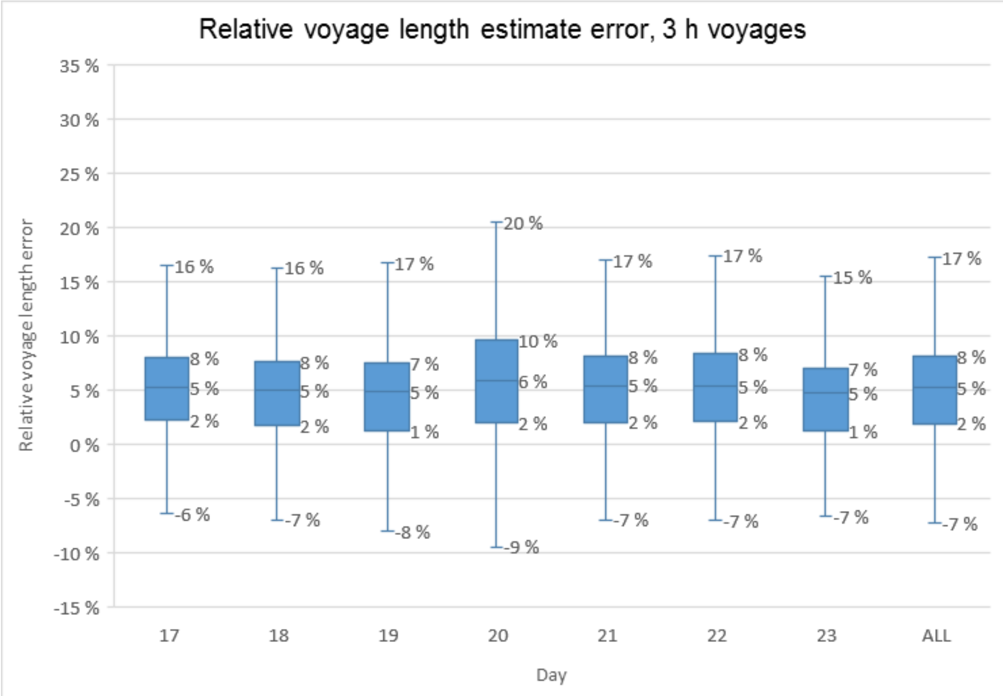
Figure 10 Predicted travel time minus observed travel time for voyages of 6 and 12 h duration. Measured as percentage within +-30 and +-60 minutes of a 6 hour voyage. For the 12h voyage a margin of +- 120 min is also included. The numbers (and bars) represent different days of the month and "all" means the overall result for all days (17 - 23.3).

In Figure 9 the accuracy of the predicted time along the track that the ships have taken, is shown as the percentage of voyage estimates that have been within 30 and 60 minutes of the actual voyage duration. The percentage is shown per day and for the whole week. Figure 9 also shows the effect of the gridcell size - a larger gridcell of 20 km instead of 2.5 km gives better results (72% vs 60% within 30 minutes of travel time estimate as an average for the whole week). For longer voyages the accuracy is degraded.

In the following, a closer analysis is done separately for the voyage length and for the voyage speed estimates.

5.1.1 Prediction of voyage length (distance)

The prediction of the voyage length from point A to B is based on choosing the path through the grid cell matrix from A to B that has the lowest total cost, i.e. the shortest voyage travel time using the speed estimates obtained from the past tracks. An analysis of the estimated track lengths shows the following distribution for the relative (predicted) track length errors:



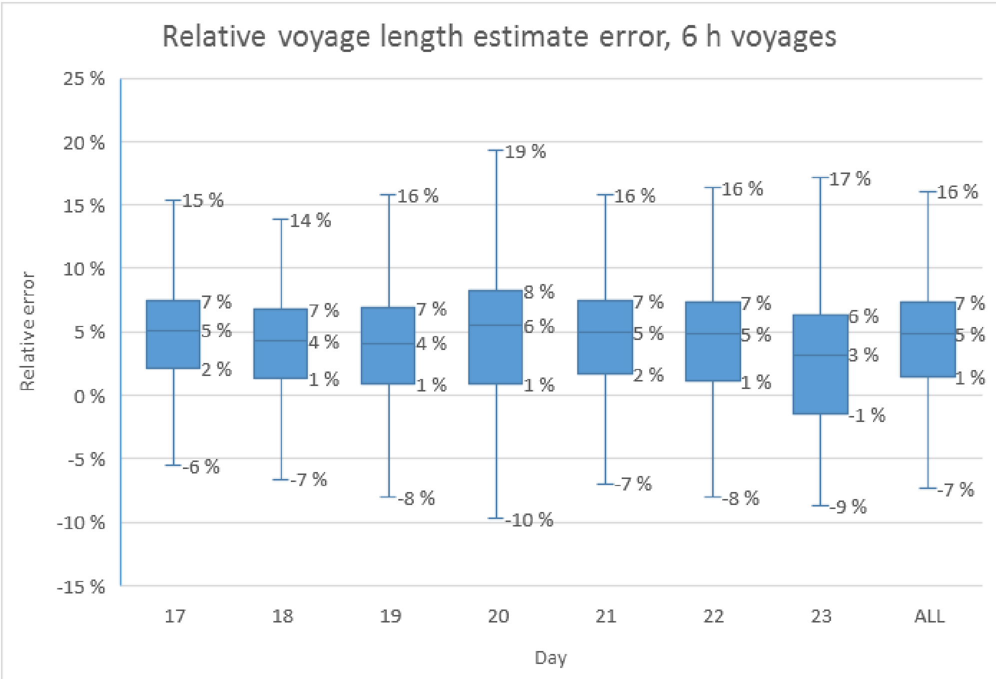


Figure 11 Relative voyage length (distance) estimation error. The Box and whiskers diagram shows the error divided per day of month and for the whole week. The estimation error is defined as predicted voyage length minus observed voyage length per observed voyage length for voyages of 3 and 6 h duration.

As the figures above show, the median of the error is +5% meaning that the median of the estimated voyage length is 5% longer than the observed voyage length. This can be attributed to the limited set of possible directions from one grid cell to another (which then affects the estimated voyage duration with the same percentage). The values are shown per day and for the whole week (ALL). There is no significant difference between the relative length error for 3 and 6 hour voyages. Also the dynamic situation during the 19 - 20.3 is indicated by the larger variations in the voyage length estimates because the routes are changing and the route finding algorithm uses past tracks for finding the shortest route.

The 5% bias can be explained by the difference in length of a “jagged” path from A to B through the matrix compared to a straight line from A to B when averaging over an even distribution of directions when going from A to B.

5.1.2 Prediction of voyage time when in ice - using actual route

For measuring the accuracy of predicting the travel time in **ice**, a subset of the voyages were selected, i.e. those with both the start and the end points north of 62.5 degree latitude. Although this is a somewhat arbitrary delineation, it was a practical way of identifying voyages that experienced mostly ice during their voyage. The estimated speed (per gridcell) was obtained from an average of the observed normalised (=relative) speed in 20 km gridcells during the past 24 hours.

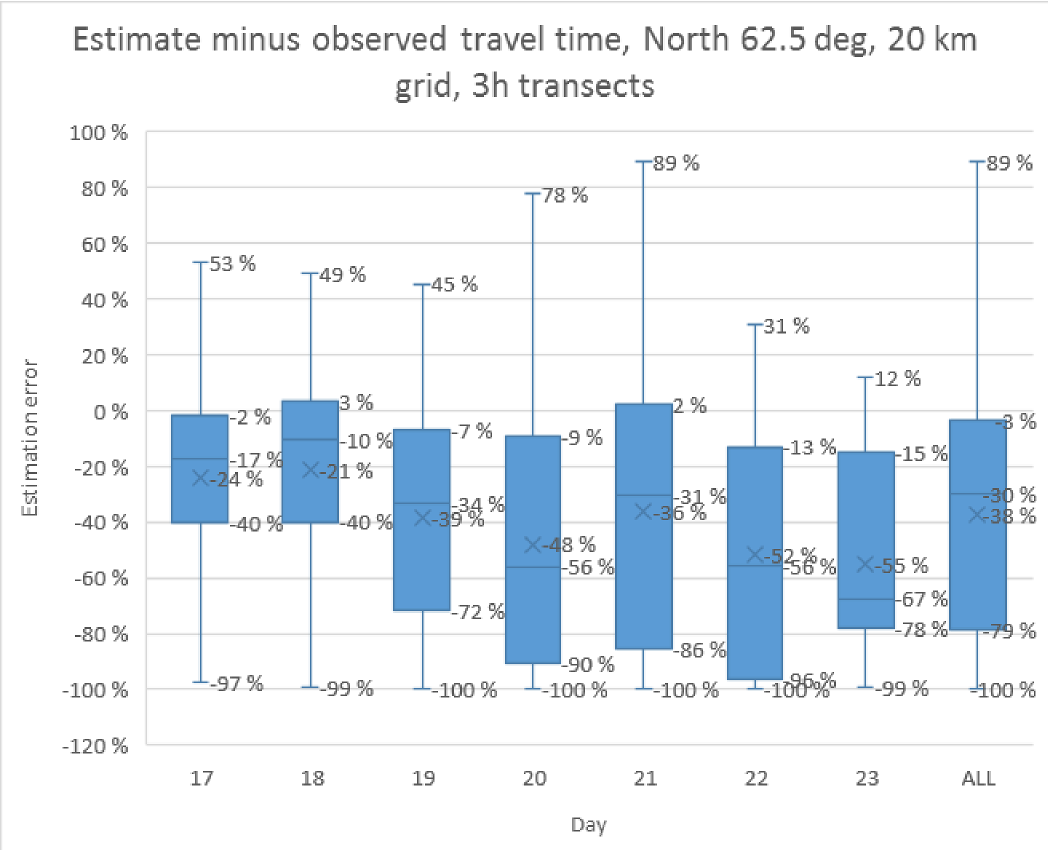


Figure 12 Relative voyage travel time estimation error. The Box and whiskers diagram shows the error per day of month and for the whole week “ALL”. The estimation error is defined as predicted voyage travel time minus observed voyage travel time per observed voyage travel time for voyages of 3 h duration. The “x” in the diagram indicates the mean value.

Figure 12 and Figure 13 show the estimation error when estimating the travel time in ice. The variations between different days indicate the variability of the ice situation. The prediction accuracy is largely dependent on the stability of the ice conditions. The median of -30% for 3 h voyages and -39% for 6 h voyages tell that the estimated time is generally underestimated by one third of the actual travel time when the voyage is in ice. This is due to the severe ice conditions when ships are stuck in ice for several hours.

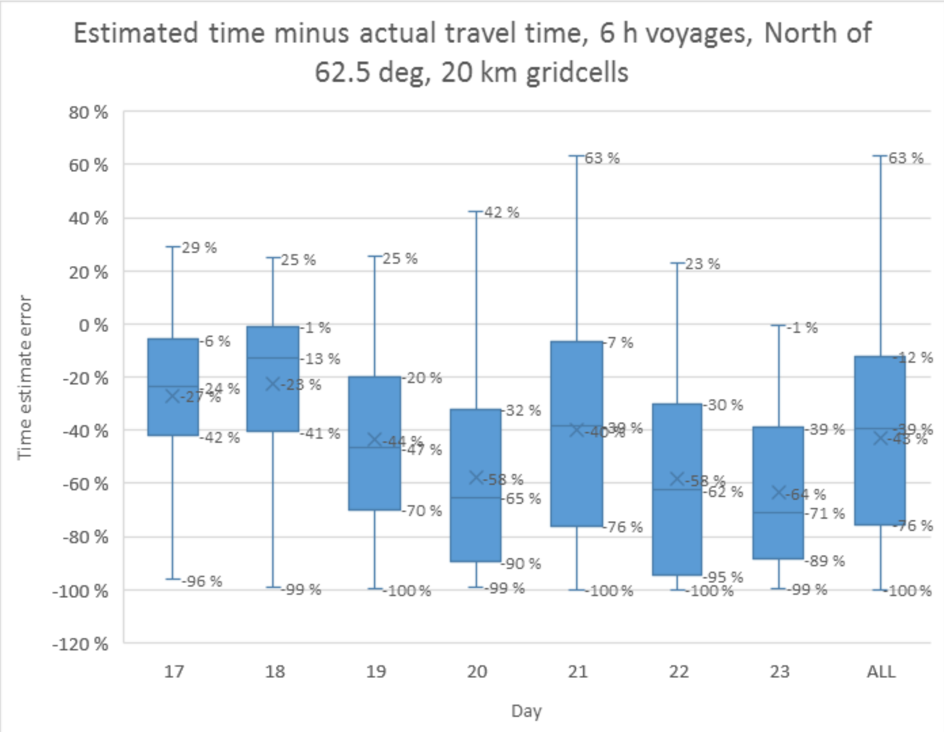


Figure 13 Relative voyage travel time estimation error. The Box and whiskers diagram shows the error divided per day of month and for the whole week. The estimation error is defined as predicted voyage travel time length minus observed voyage travel time length per observed voyage travel time length for voyages of 6 h duration.

5.1.3 Prediction of voyage time - including route and speed prediction.

The overall prediction accuracy of the algorithm is summarized in the figure below. The metrics for accuracy is the relative number of predictions that have been within a predefined time limit. In the analysis the voyages are separated into those that are mainly in open water (or ice with low concentration) and those that have to pass through heavy ice fields. The analysis shows that 84% of 3h voyages are predicted correctly within +-30 minutes when the voyage has been in open water. When in ice, the situation changes. Still, of those (in ice) 54% of the 3h voyages are predicted correctly within 60 minutes tolerance. The longer voyages suffer from larger errors, due to increased uncertainties in the ice field causing longish waiting times. These times are not taken well into account in the present version of the algorithm.

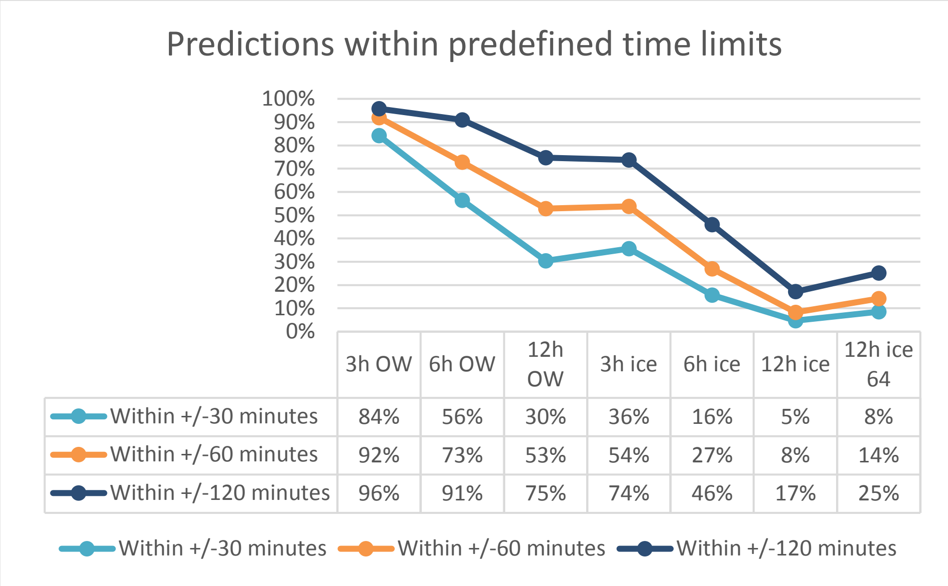


Figure 14 Relative voyage time estimation error.
OW: Voyage in open water conditions – both the start and the end point of the voyage are below 62.5 degrees North..Ice: Voyage in ice. Both start and end points of the voyage are above 62.5 degrees North. For 12h voyages this means that the ship has been stuck in ice for some time.
Ice 64: Voyage in ice, but now either start or end point is above 64 degrees North

Table 2 Summary of relative error distribution for Open water voyage time predictions (column ALL in Figure 15). Q1 is the lower quartile and Q3 is the upper quartile.

Voyage	min	Q1	Median	Mean	Q3	max
3 h	-26 %	-6 %	2 %	3 %	8 %	28 %
6 h	-28 %	-8 %	1 %	-1 %	6 %	27 %
12 h	-36 %	-12 %	-3 %	-5%	4 %	21 %

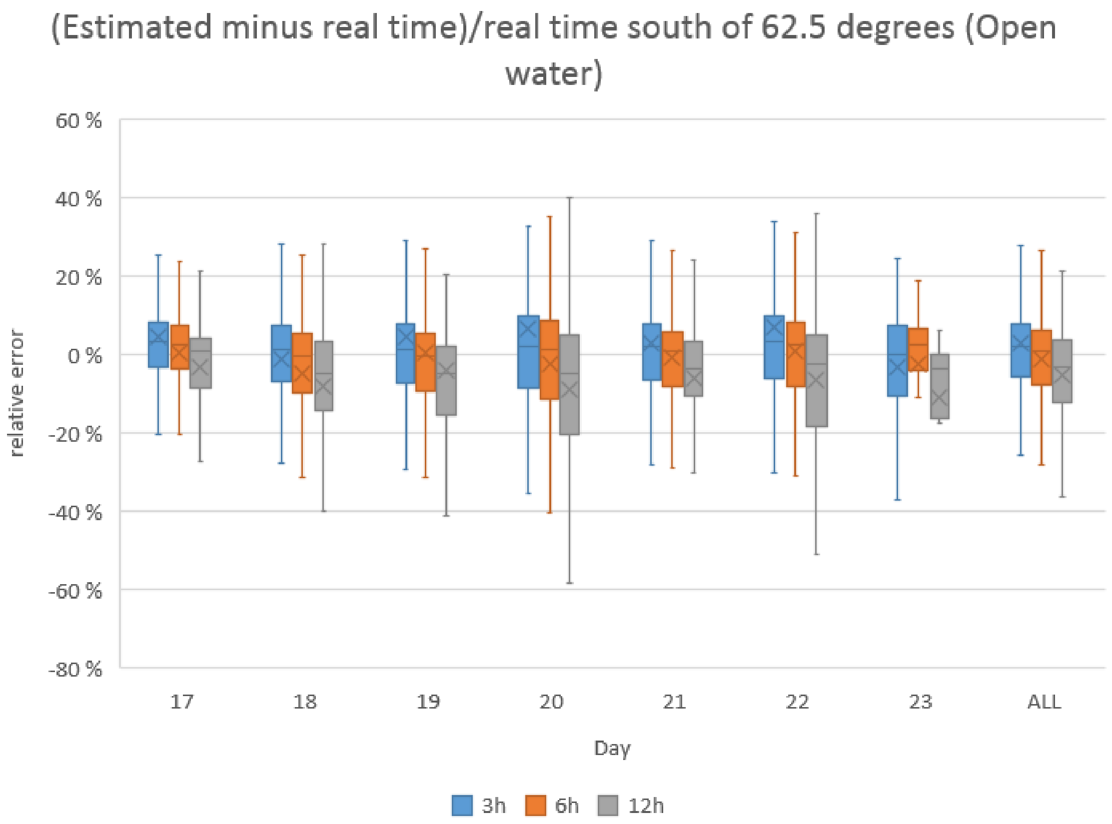


Figure 15 Relative voyage time estimation error for voyages south of 62.5 degrees North (open water conditions). The Box and whiskers diagram shows the error divided per day of month and for the whole week. The estimation error is defined as predicted voyage duration minus observed voyage duration divided with the observed voyage length for voyages of 3, 6 and 12 h duration.

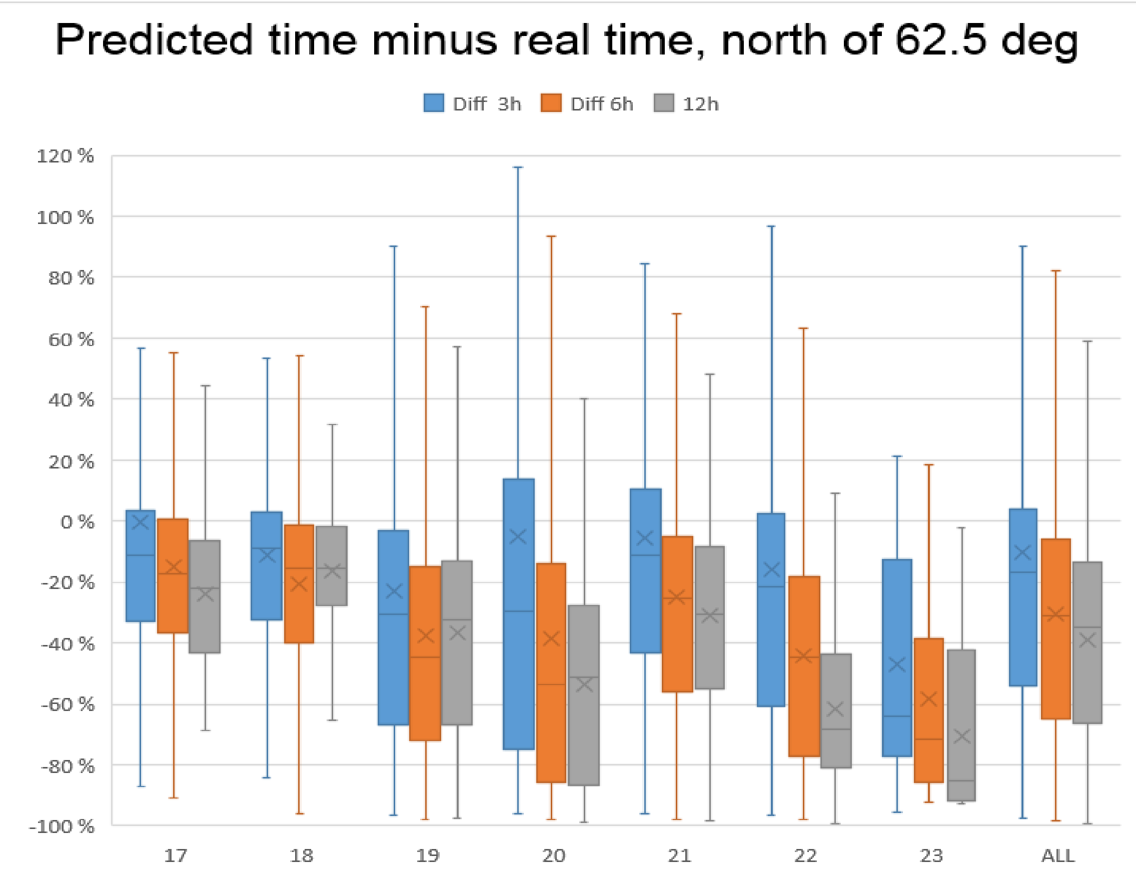


Figure 16 Relative voyage time estimation error for voyages ***north*** *of 62.5 degree latitude (voyage goes through ice). The Box and whiskers diagram shows the error divided per day of month and for the whole week. The estimation error is defined as predicted voyage duration minus observed voyage duration divided with the observed voyage length for voyages of 3, 6 and 12 h duration.*

As indicated in Figure 16 that shows the voyage time estimation error for voyages in ice, the relative accuracy interval is about equal for 3, 6 and 12 h voyages - with daily variations. The median for 3h voyages is about -17%, which is 30 minutes too optimistic. The longer voyages perform worse. (-31% or -111 minutes, -35% or -252 minutes)

When doing the comparison between estimated voyage times and observed voyage times along the observed route, the results could only be obtained for voyages where there had been previous vessels passing the same gridcells as the observed route. When the route is an estimated route, then only the starting and endpoints (gridcells A and B) are required (plus finding a way to reach B from A). The number of cases where these conditions were true correspond to the number of voyages in the table below. The percentage in the table below illustrates the ratio of found trails compared to the all trails. For long voyages and for small gridcells, the number of not found voyages increased significantly (Table 3).

Table 3 Summary of analysed voyages in the study

Number of voyages	No track found	Percentage found	grid size (km)	Length(h)	route: observed/estimated
4069	6783	37 %	2.5	3	observed
10282	571	95 %	20	3	observed
7080	731	91 %	20	6	observed
3220	864	79 %	20	12	observed
10158	708	93 %	2.5	3	estimated
7351	481	94 %	2.5	6	estimated
3794	298	93 %	2.5	12	estimated

5.1.4 Results of estimating speed prediction accuracy without ice forecast information (the past track algorithm)

The past-track algorithm that has been tested, works reasonably well in conditions where ships are not stuck in the ice. In severe ice conditions, where ships are idling for hours waiting for icebreaker assistance, the predictions contain high uncertainties. This situation is, however, not the usual case for normal winters. Improving the estimate by handling separately the cases when ships have been stuck in the ice, could improve the accuracy.

5.2 Estimating ship speed from ice condition information

The process of estimating ship speed from ice conditions has been analysed in several publications. In this study, a machine learning approach has been selected. The task is done according to the flowchart in Figure 17.

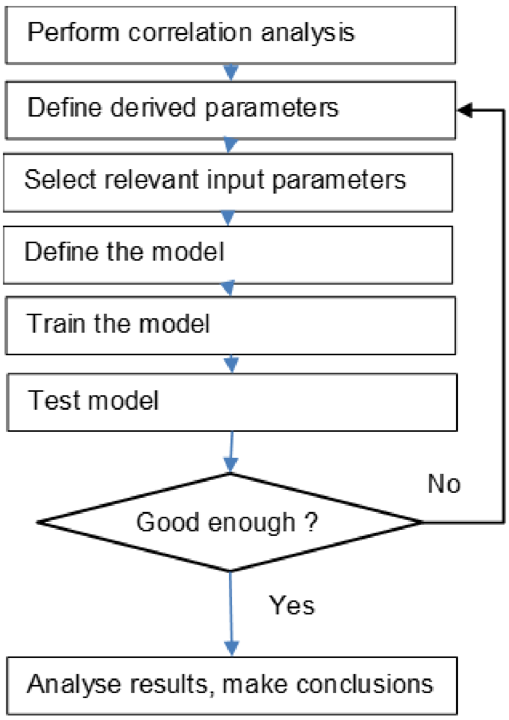


Figure 17 Flow chart of ship speed estimation algorithm development

5.2.1 Selection of input parameters

The first boxes in the analysis can be considered as part of Feature engineering which are the steps before feeding the data to a machine learning algorithm. The purpose is to use domain knowledge and select & combine the input parameters to represent significant features that affect the output variable.

Input parameters

The input parameters that have been selected are the following:

Ice conditions (from reanalysis data). The ice parameters from the reanalysis data (see Table 1) are numerical values that are scaled and normalized.

Table 4 Ice conditions

Name	**Unit**	**Description**	**Comment**
htotal	m	Total thickness of ice, sum of hi	normalized
atotal	**-**	total concentration, sum of ai	normalized
v_magnitude	m/s	magnitude of (ui, vi) - ice drift speed	normalized
hri	m	ridged ice height	normalized
ari	-	ridged ice concentration	normalized
hra	m	rafted ice height	normalized
ara	-	rafted ice concentration	normalized
dsigdx	N/m	stress x-derivative	normalized
dsigdy	N/m	stress y-derivative	normalized

Proximity of other ships: two parameters are here used to indicate the proximity of other ships: a) time since last visit in the same gridcell in the same or opposite direction (Course over ground difference between -20 and 20 degrees or between 160 and 200 degrees) and b) ship in convoy. The time since last visit is bucketised to discrete time intervals: 0 - 30 minutes, 30 - 60 minutes and then in 1 hour intervals up to 6 hours. Ship in convoy is a Boolean parameter. A ship is in convoy if another ship is seen in an angle +- 20 degrees in front of the ship and the distance to this ship is less than 4 km. (In an earlier study, when using this criterion, 87% of the ships registered as being assisted by the icebreaker information system IBNet, were identified correctly).

Table 5 Ship parameters

Name	Unit	Description	Comment
iceclass	category	Unknown, III, II, IC, IB, IA, IAS	From IBNet
ibnet_speed	knots	Nominal Open water speed	From IBNet, normalized
ibnet_shiptype	category	type of ship (Bulk, Container, Tanker, Passenger, Icebreaker, RORO, Tug)	Classification according to IBNet
length	m		From IBNet, normalized
breadth	m		From IBNet, normalized
DWT	tonnes	Deadweight	From IBNet, normalized
power	kW	Installed propulsion power	From IBNet, normalized

5.3 Correlation analysis

In Table 6 the relevant parameter candidates are listed in decreasing order of the absolute value of the median of the linear correlation with the relative ship speed variable. The correlation varies from year to year. (The parameter *h_mean_actual* is the calculated thickness of the ice sheet calculated as average ice thickness per ice concentration. This parameter is highly correlated with the ice thickness and is sensitive to errors when the ice concentration is low so it has been left out as input parameter in the models).

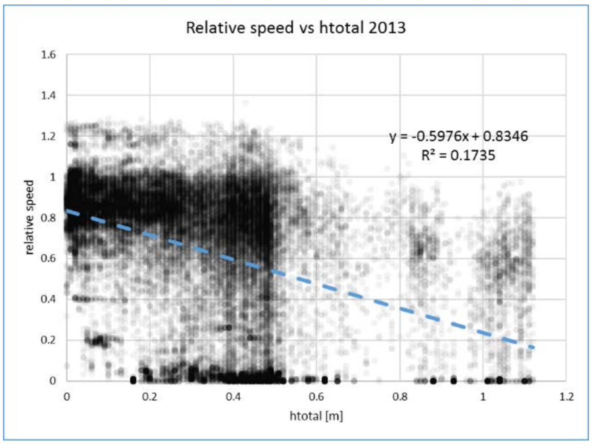
Table 6 Correlation analysis (linear correlation) of the parameter candidates with respect to the relative speed of the ships. ***Median, max, min, Maximum absolute value (Max(abs))*** *and* ***difference between Max and Min*** *refer to the correlation coefficients from the three years that were studied.*

Parameter	2013	2014	2016	Median	Max	Min	Max(abs)	Max - Min
h_mean_actual	-0.45	0.00	-0.26	-0.26	0.00	-0.45	0.45	0.44
htotal	-0.42	-0.40	-0.35	-0.40	-0.35	-0.42	0.42	0.06
atotal	-0.28	-0.31	-0.30	-0.30	-0.28	-0.31	0.31	0.03
dsigdx	0.30	0.28	0.20	0.28	0.30	0.20	0.30	0.10
dsigdy	0.30	0.29	0.16	0.29	0.30	0.16	0.30	0.13
hri	-0.27	-0.22	-0.01	-0.22	-0.01	-0.27	0.27	0.25
ari	-0.26	-0.22	0.00	-0.22	0.00	-0.26	0.26	0.25
v_magnitude	0.23	0.04	0.19	0.19	0.23	0.04	0.23	0.18
ibnet_speed	0.00	-0.10	-0.20	-0.10	0.00	-0.20	0.20	0.19

dwt	0.02	-0.18	-0.09	-0.09	0.02	-0.18	0.18	0.20
ara	-0.08	-0.15	0.03	-0.08	0.03	-0.15	0.15	0.18
hra	-0.14	-0.15	0.00	-0.14	0.00	-0.15	0.15	0.14
power	0.14	-0.07	-0.11	-0.07	0.14	-0.11	0.14	0.25
build_year	0.06	-0.04	0.14	0.06	0.14	-0.04	0.14	0.18
time_from_prev_h	-0.13	-0.05	-0.06	-0.06	-0.05	-0.13	0.13	0.08
ibnet_draught	0.01	-0.13	-0.08	-0.08	0.01	-0.13	0.13	0.14
breadth	0.12	-0.11	-0.07	-0.07	0.12	-0.11	0.12	0.23
in_convoy	0.10	-0.04	-0.06	-0.04	0.10	-0.06	0.10	0.16
length	0.10	-0.09	-0.07	-0.07	0.10	-0.09	0.10	0.19

Scatterplots:

The following figures show scatterplots of some of the parameters vs relative speed of the ship.



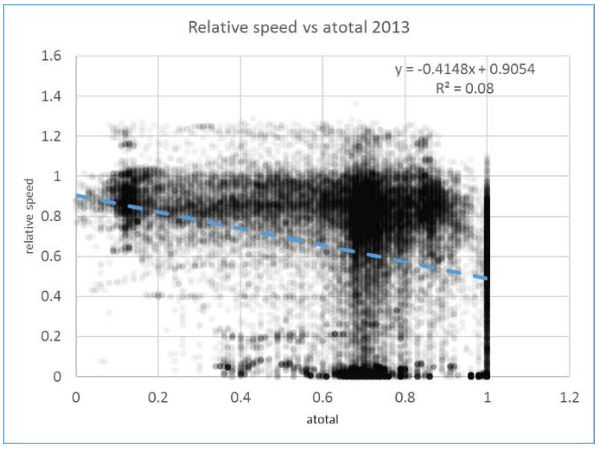


Figure 18 Relative speed vs Total ice thickness (htotal) and Total ice concentration (atotal) for the 2013 data

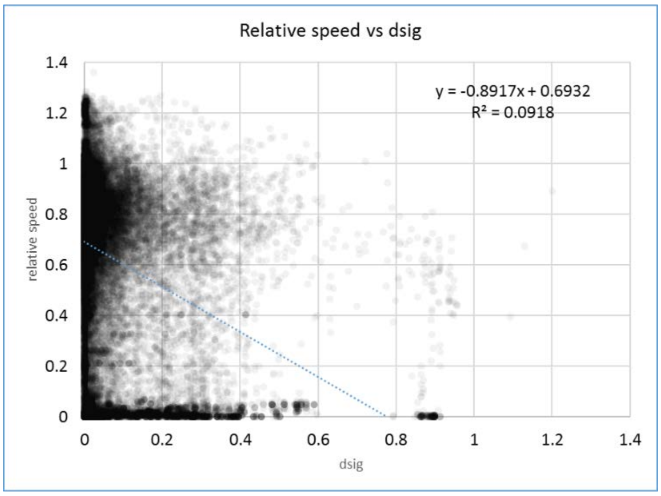


Figure 19 Relative speed vs total stress derivative $dsig = \sqrt{dsigdx^2 + dsigdy^2}$

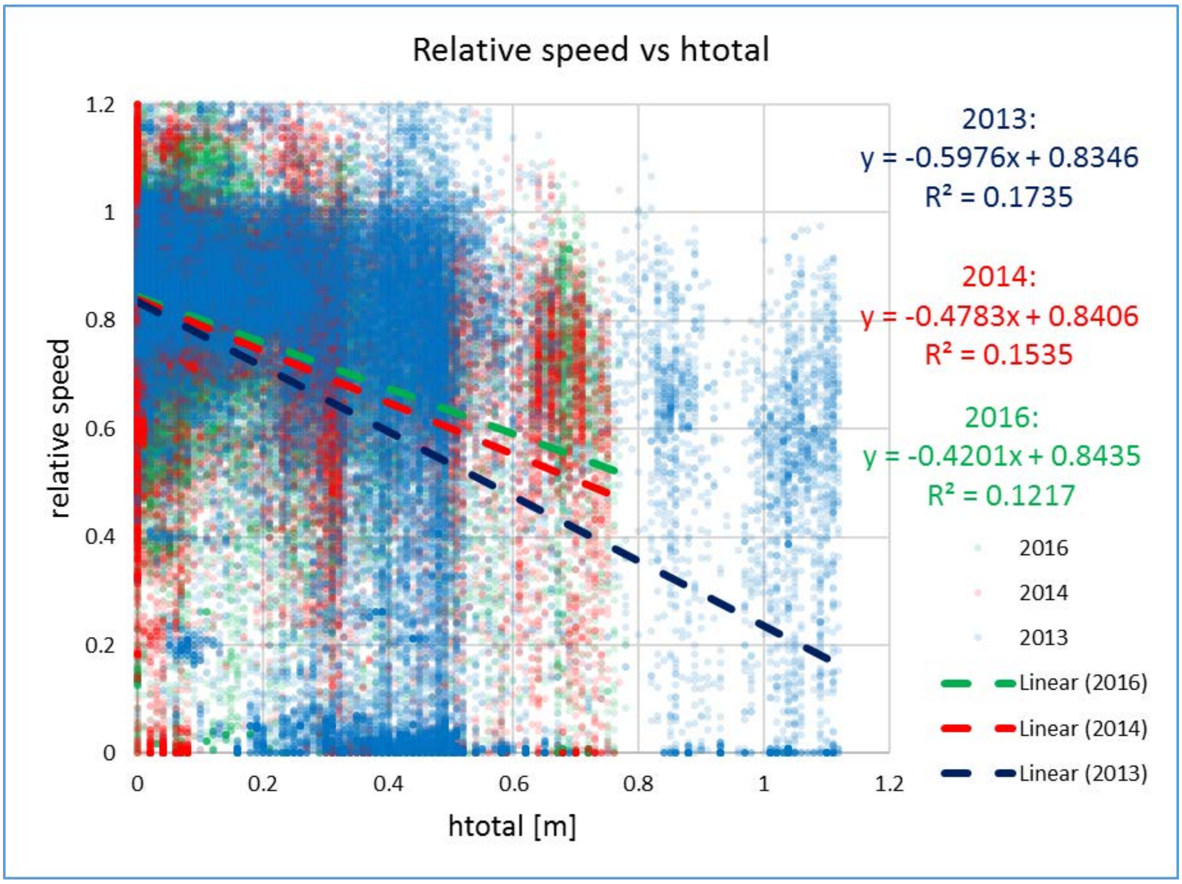


Figure 20 Relative speed vs htotal. The years 2013, 2014 and 2016 are shown in different colours.

5.4 About training and testing

The target output variable is ship speed. Thus the estimated ship speed is compared to the measured ship speed given the ship parameters and the ice conditions as described by the ice model. The data is divided into a *training set* and a *dev set* by random shuffling. A separate *test set* is then used to test the validity of the model. The first 5 days of data for the target weeks in 2013, 2014 and 2016 are used for training and developing the model. Validation is then done using data of the 6^{th} day.

This setup mimics the situation where a model is trained using the most recent data, and the model is then used to predict the ship speed on a subsequent day given the prevailing ice conditions then. The method also eliminates the effect of cross-correlation between samples that are time wise adjacent and thus correlated.

Table 7 Summary of the data used

Year	**Size of training set**	**Size of dev set**	**Size of test set**
2013	38406	4268	7284
2014	49992	5554	6804
2016	50159	5574	8529

5.5 Linear regression model

In a linear model, the observed variable is assumed to have a linear dependency of the input parameters. One possibility to handle categories is to treat them as separate parameters using one-hot encoding. The results from such an analysis are shown in the results later.

5.6 Feed-forward neural network model

Considering the number of input data records, and a rule-of-thumb, a feed-forward neural network consisting of two hidden layers has been used. Comparative runs have been performed using the following parameters:

Optimizer when learning: ProximalAdagradOptimizer
learning_rate=0.3,
l1_regularization_strength= 0.001 .. 0.004
hidden_units = [100, 75, 50, 25]

6. Results

6.1 Comparison of predictions (track-based algorithm vs feed-forward neural network)

To compare the estimation algorithms, the RMSE of the predicted speed as well as the correlation coefficient of the predicted speed vs observed speed have been used as metrics. The setup is somewhat different for the track-based algorithm than for the feed-forward neural network. The track-based algorithm uses data collected up to the last hour before the observation whereas the neural network is trained with data from the days before the test day. (Another way would be to select a test set by randomly selecting observations among all of the data. However, there is a strong correlation between adjacent observations, whereby the training set is not independent of the test set).

For the track-based algorithm, the comparison was made using two different grid sizes: 2.5 km and 20 km. The smaller gridsize gave a higher correlation coefficient (R^2) than the 20 km one (0.32 vs. 0.27). Note! In the analysis, only relative speed below 0.7 are included to filter out the trivial case of ships steaming with an open water speed or near such a speed.

The RMSE for the 2.5 km gridsize was 5.77, and 6.52 for the coarser gridsize

Note that these predictions do not use any ice condition data as input.

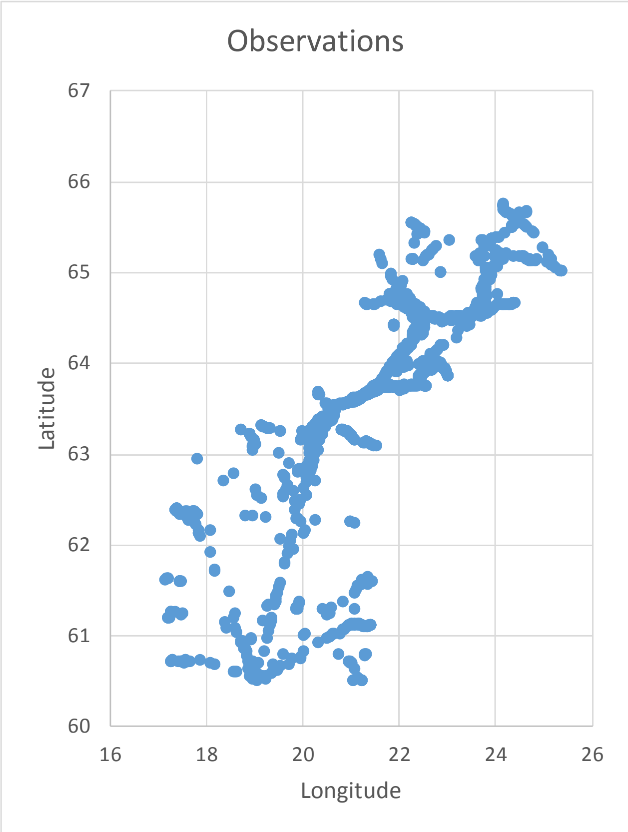


Figure 21 Locations of speed observations for the track-based algorithm during 19 - 22.3.2013. 2232 observations were used for the comparison. The grid size was 2.5 km.

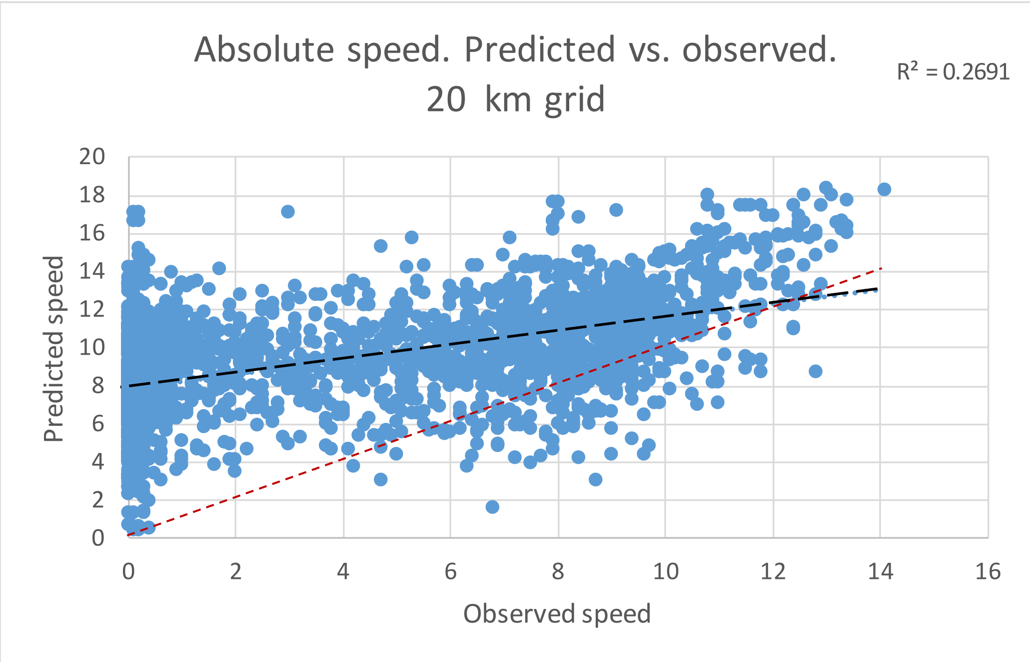


Figure 22 Predicted speed vs observed speed for the track-based algorithm. 20 km gridcells. 19 - 22.3.2013. Only relative speeds below 0.7 times open water speed included. (The red dashed line is a reference line with the slope 1).

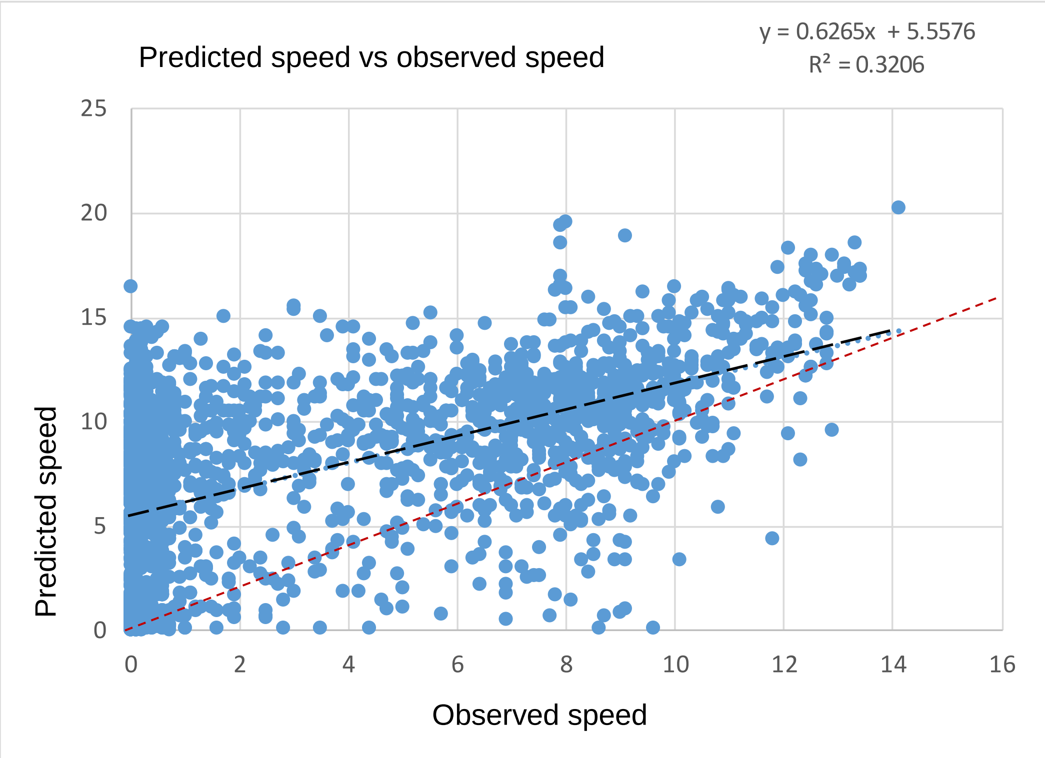


Figure 23 Predicted speed vs observed speed for the track-based algorithm. 2.5 km gridcells. 19 - 22.3.2013. Only relative speeds below 0.7 times open water speed included. (The red dashed line is a reference line with the slope 1).

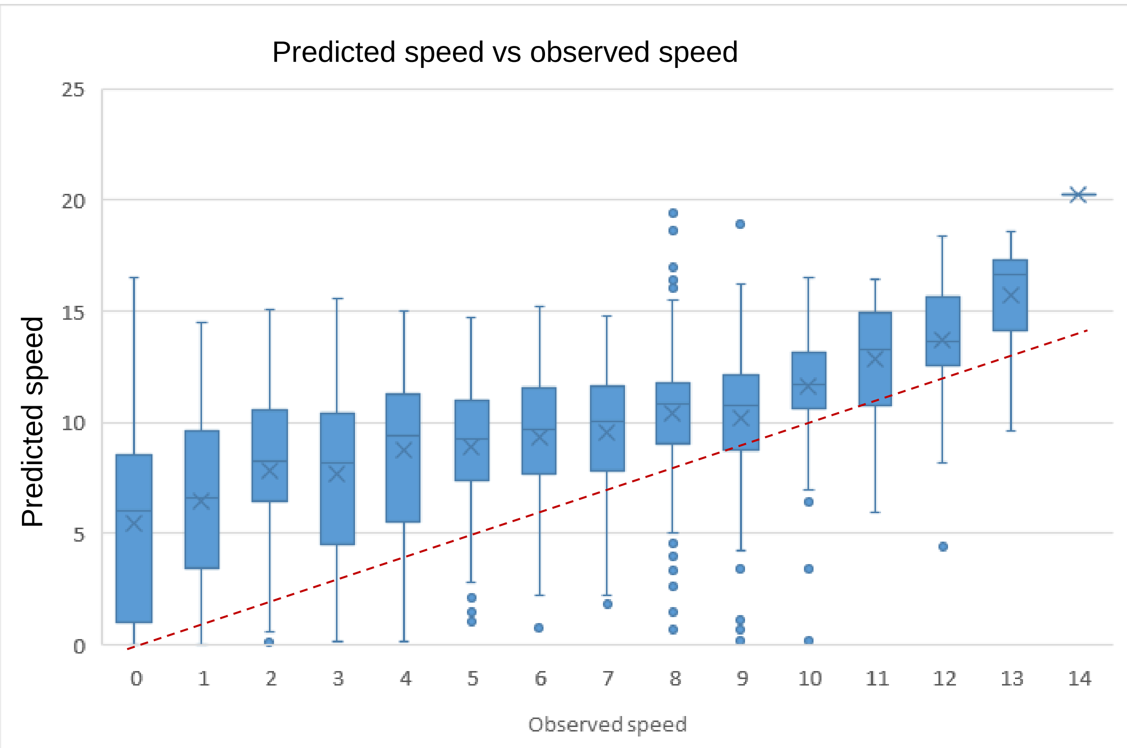


Figure 24 Predicted speed vs observed speed for the track-based algorithm. 2.5 km gridcells. 19 - 22.3.2013. Only relative speeds below 0.7 times open water speed included. (Same as Figure 23)

Then we tested how well we can estimate the speed using ice condition data and the ship particulars and modelling using a feed-forward neural network.

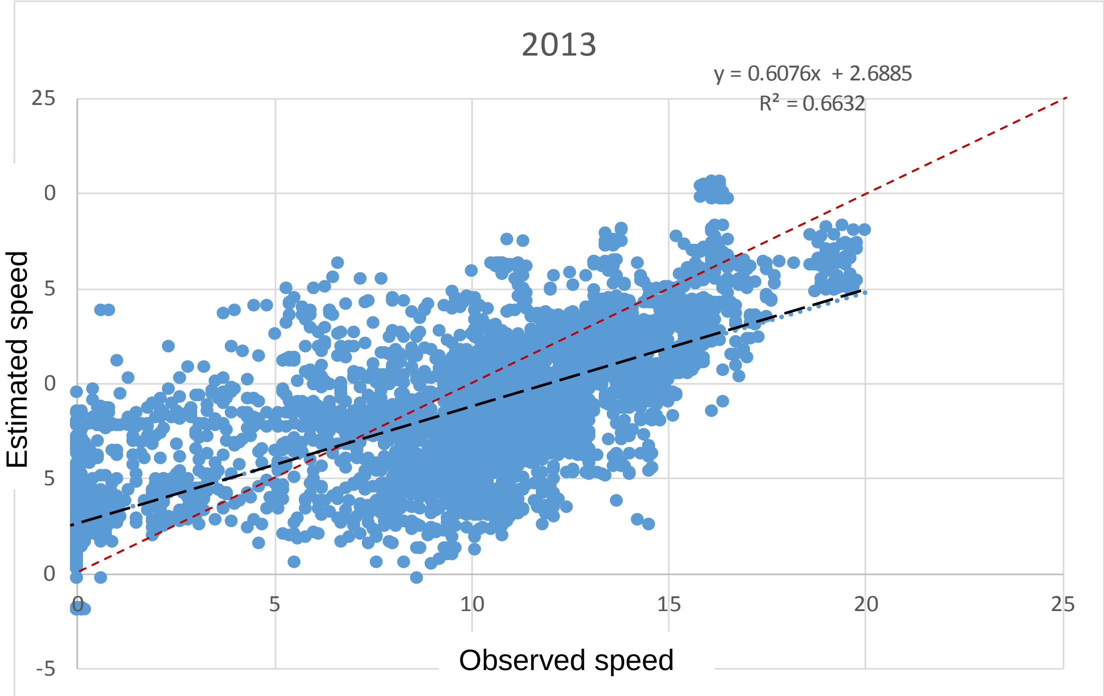


Figure 25 Estimated speed vs observed speed for feed-forward neural network where the speed is estimated based on ice model data and ship particulars. Training based on 19 - 21.3.2013, test on 22.3.2013 data. (The red dashed line is a reference line with the slope 1).

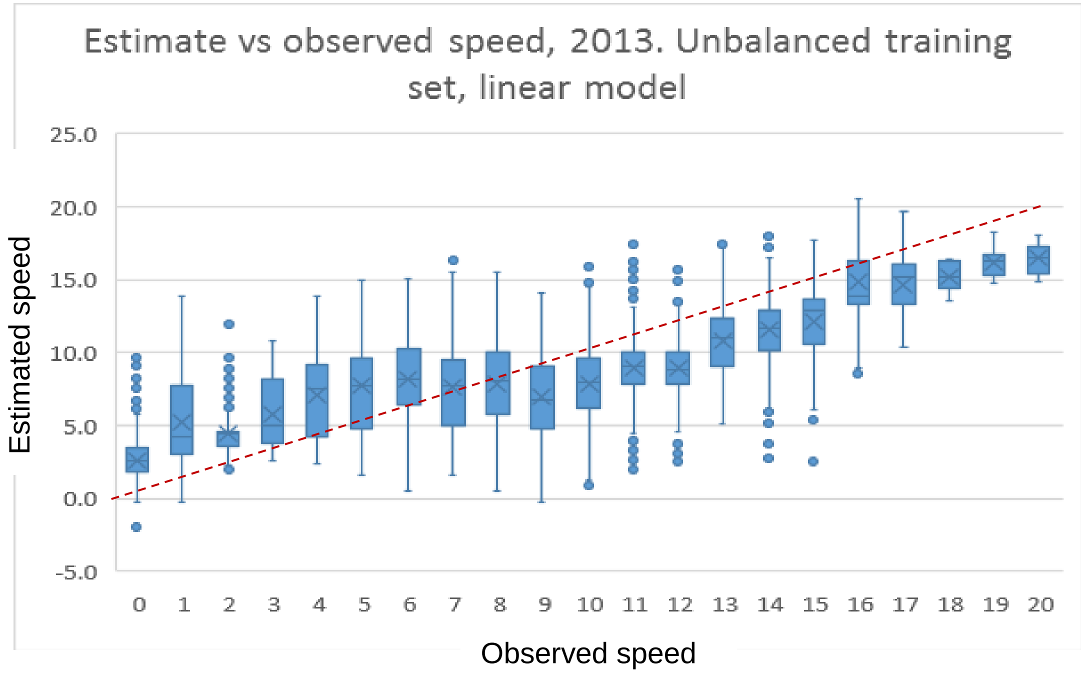


Figure 26 Same as Figure 25

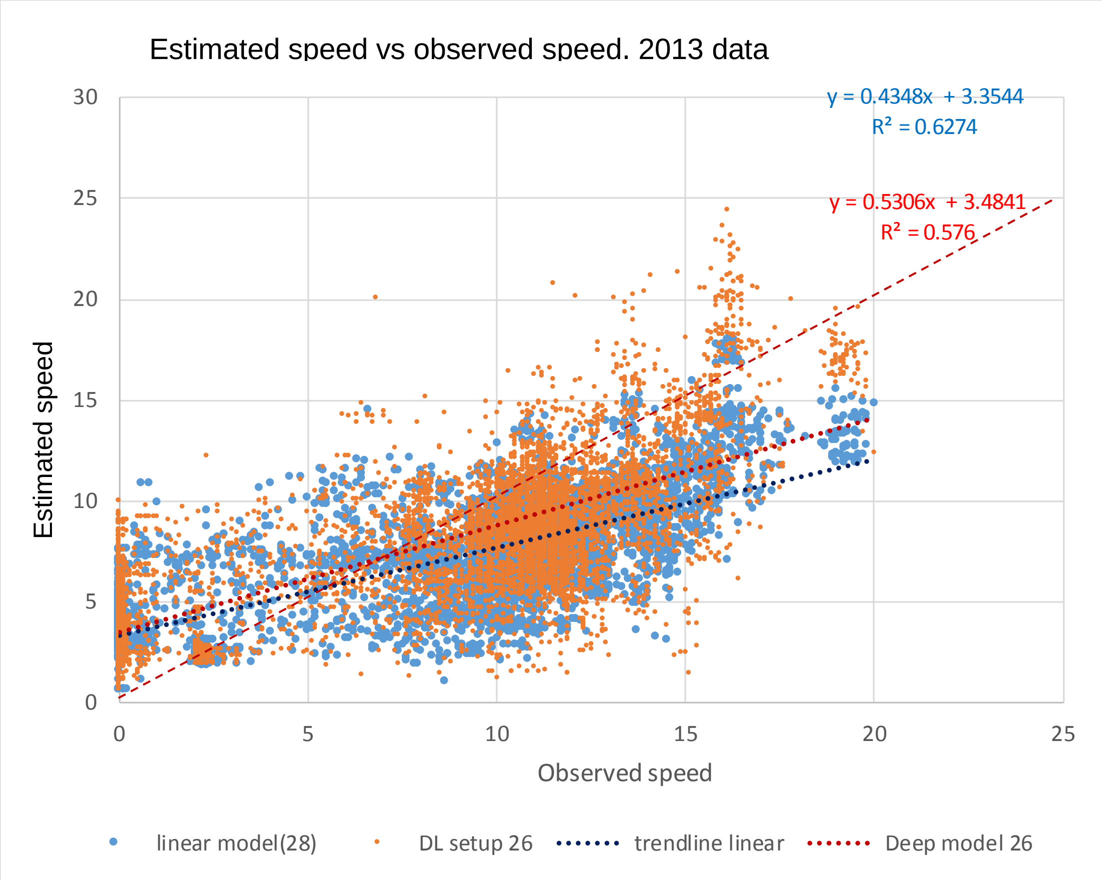


Figure 27 Estimated speed vs observed speed for two types of feed-forward neural networks where the speed is estimated based on ice model data and ship particulars. Training based on 19 - 21.3.2013, test on 22.3.2013 data. The dashed line is a reference line (observation = estimation).

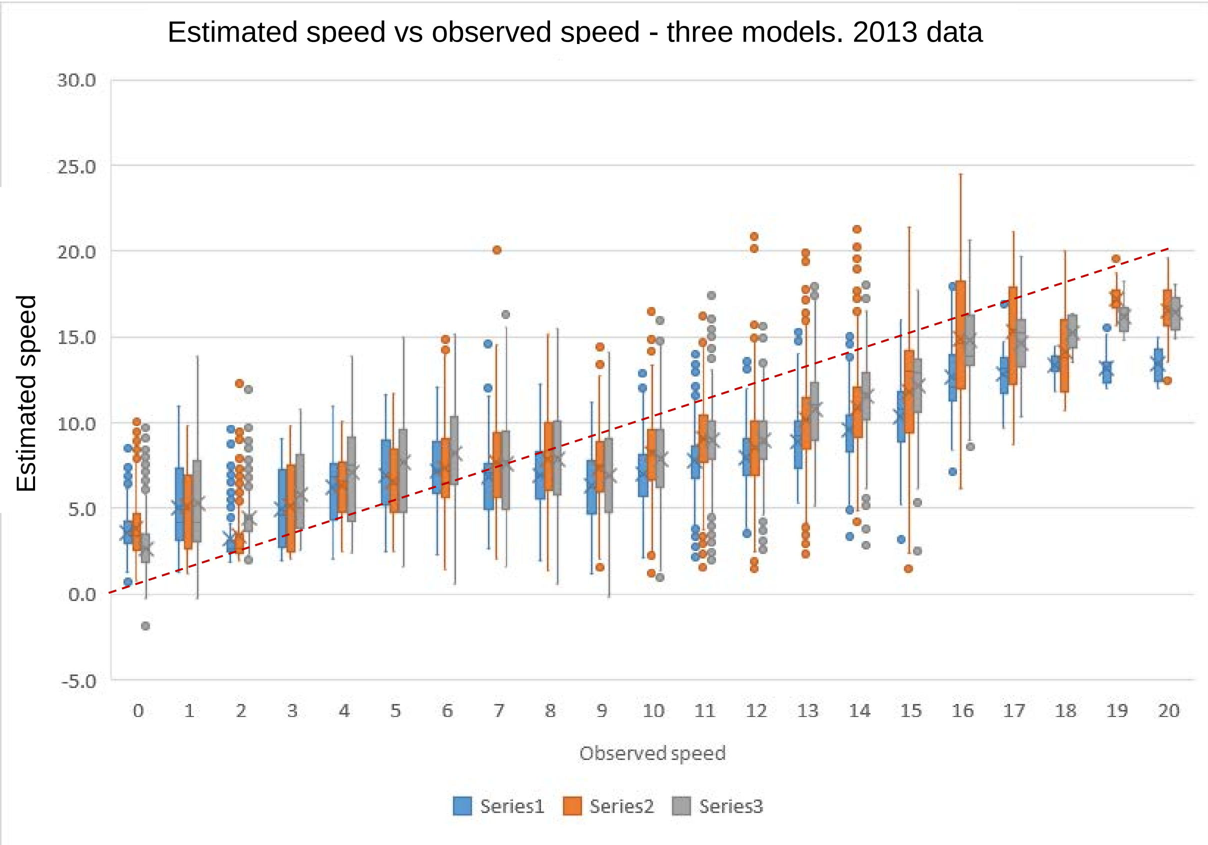


Figure 28 Estimated speed vs observed speed for three types of feed-forward neural networks where the speed is estimated based on ice model data and ship particulars. Training based on 19 - 21.3.2013, test on 22.3.2018 data. Series 1 is a linear model, series 2 is a neural net with two hidden layers. Series 3 is a linear model, but the training set is used without compensation for uneven distribution of speed classes. (The red dashed line is a reference line with the slope 1).

The RMSE for the neural network with the best set of parameters has varied between 3.57 and 3.92. RMSE for the linear model was 3.82, 3.28 when an unbalanced training set was used.

2014 results:
The RMSE for the 2014 situation is 3.36

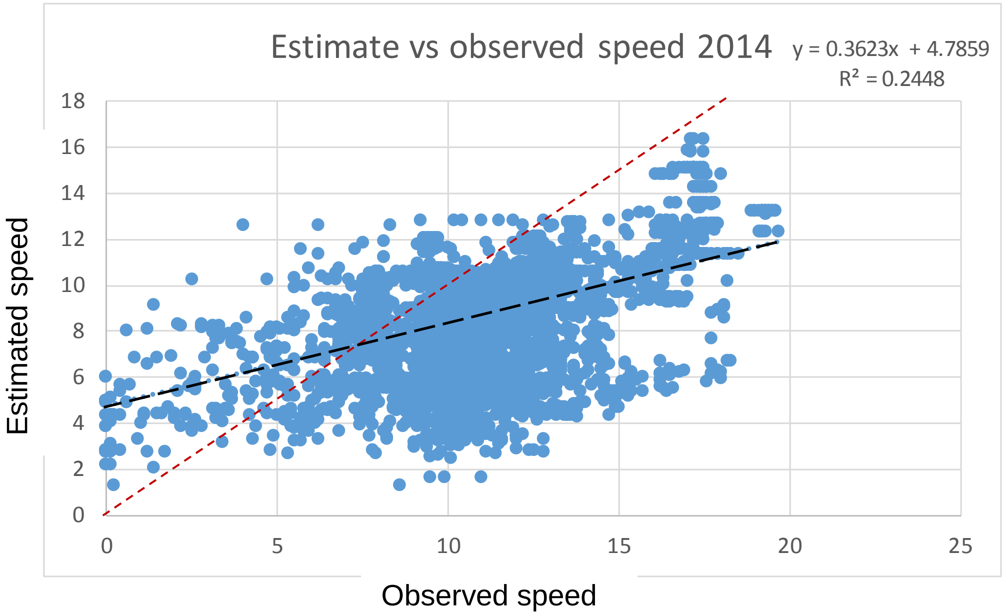


Figure 29 Estimated speed vs observed speed 2014. Linear model.

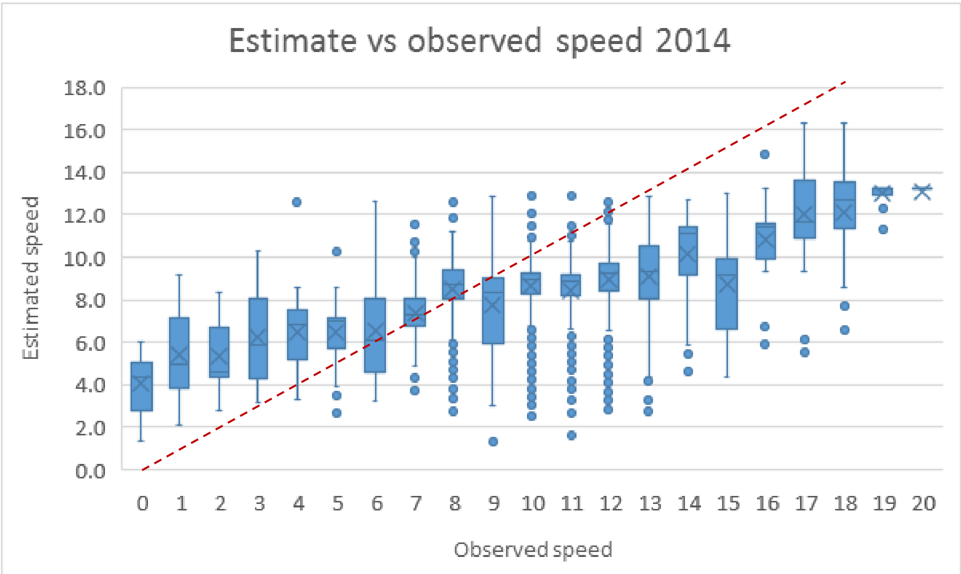


Figure 30 Estimated speed vs observed speed 2014. Linear model.

2016 situation:
The RMSE for 2016 situation is 3.96

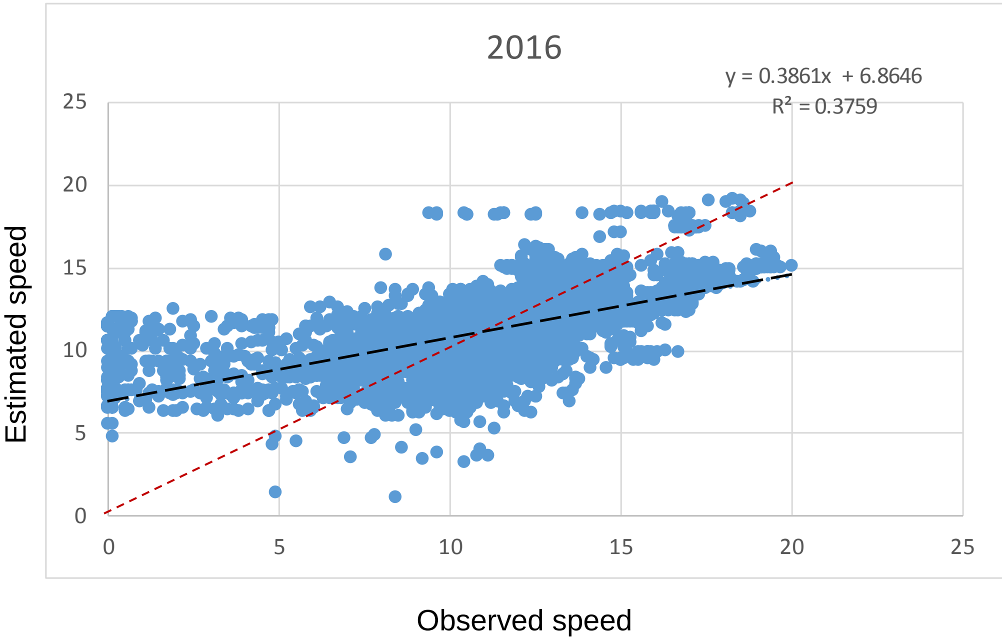


Figure 31 Estimated speed vs observed speed 2016. Linear model.

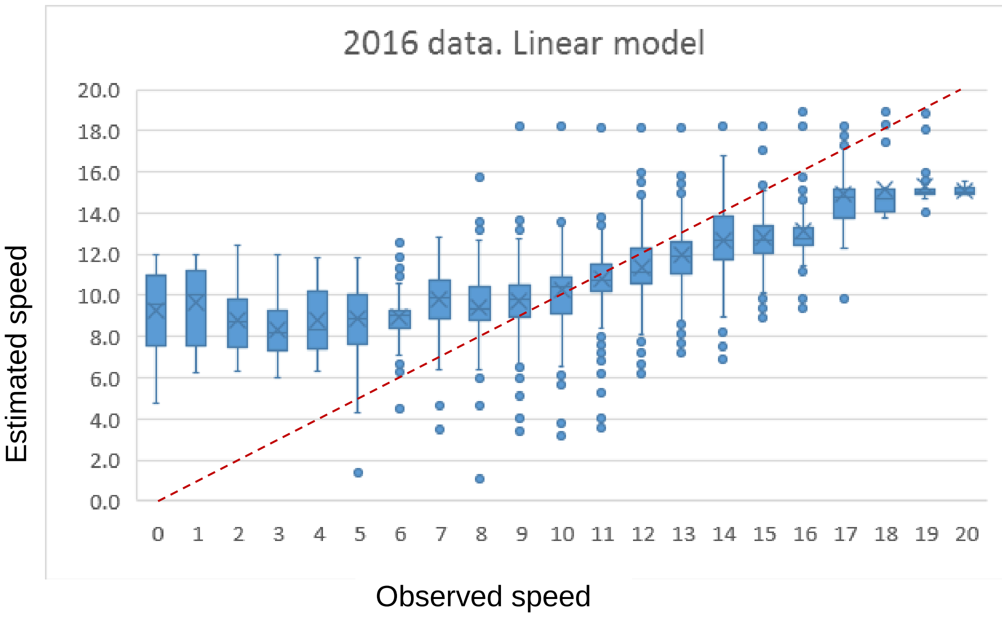


Figure 32 Estimated speed vs observed speed 2016. Linear model.

7. Discussion

The study has concentrated on an analysis of the track-based voyage time estimation algorithm. As the data covers only limited periods of the winter, the results are difficult to extrapolate more generally. Obvious is that the estimation algorithm works fairly well in static situations where both the tracks as well as the ice conditions are stable. Another difficulty is the effect on situations where ships are beset in the ice and thus totally dependent on icebreakers to arrive.

Using reanalysed ice data to describe the ice conditions do capture the essential elements that affect ship speed only partly as most ships proceed using tracks made by other ships and the conditions of these tracks are not described in the ice model. The data driven approach (track-based algorithm) includes the capability to monitor the observed effects of the ice conditions on ship speed. However, in the vicinity of other ships, there are other reasons that affect the speed of the ship than the ice conditions. From a research point-of-view, excluding these situations by identifying the relative distances to other ships, would make an analysis easier. But for the user that is interested in an estimate of the travel time, such exclusions make the results less valuable.

What can be seen is that the difficulty lies in predicting speeds that are below half of the open water speed. This is due to larger variations when ships are significantly affected by the ice conditions.

Also, the effects of our pre-processing of the AIS data could be studied more closely. We have interpolated the positions and speed of the ships to five minute intervals - which makes proximity calculations easier and also reduces the amount of data. What we lose, are the temporal variations in speed and COG. This information has not been used as input variables in the study.

In an estimation of the travel time, the length of the voyage to the destination can be estimated rather accurately. The systematic bias in the grid-based algorithm can be compensated for, if considered necessary. Some adjustments in cases where the routing is changed significantly, should be thought of.

Within the time and resources allocated for this study it has not been possible to try out hybrid solutions where the track based estimation would have been combined with the ice model input.

Also a more extensive test sequence is needed to validate the forecasting possibilities when the model is continuously trained with data from a recent history.

When evaluating the operational possibilities, it would also be necessary to look into the uncertainties in the current operational ice forecasting models compared to the reanalysed data that has been used in this study.

And finally - a travel time estimating service would need to include a simulation element to estimate the waiting times that would occur when ships cannot proceed on their own through the ice field.

8. Conclusions

Based on the RMSE and R2 values for how well the algorithms are able to predict the ship speed in prevailing ice conditions, it seems that the predictor using ship particulars and ice model parameters performs better than the track-based algorithm. However, neither of these approaches are suitable for the purpose of predicting the travel time taking into account the waiting times. Also, the ship speed estimating algorithm should be compared to the best multivariate models and validation performed using a larger test set.

The best results may be achieved by incorporating further input sources like satellite images.

The route estimation part seems to work reasonably well, but the travel time estimation would require other approaches like simulations, which requires much more input to be feasible.

An interesting study would be to test the influence of being in a convoy and what the effects of moving in a channel are. Within this study, no significant parameter combinations have been found to improve the predictive capability of the model.

Returning to our research questions:

Question	Why	Result
Is it possible to predict slowdown of ships by monitoring slowdown of other ships that have transited the same route during the past 1 - 24 hours?	To get a quantitative measure of the prediction accuracy of an algorithm that is based on a simple nowcasting model	Yes it is possible to estimate, but the accuracy is not that good - or they are good only in stable conditions. Accuracy statistics should be calculated over the whole winter. When ships run the risk of being stuck, the predictions are difficult to obtain
Can we improve the prediction accuracy by using numerical ice condition models?	To get a quantitative measure of the prediction accuracy of an algorithm that is based on numerical models of the ice (in the Baltic Sea)	Yes, the numerical forecasts can be used to predict slowdowns, but do not help to estimate the travel time if the ship is stuck. However, the forecasts could be used to evaluate the risk of being stuck. We have done some trials, but not done extensive statistical studies on the prediction accuracy.

9. Summary

In this study we have examined the accuracy of an algorithm that predicts the slowdown of ships based on observed slowdowns during the past 24 hours. We have compared this method with the method based on a machine learning algorithm that seeks to predict the speed of a ship based on the prevailing ice conditions. The analysis has shown that it is possible to use the past tracks of ships to predict both the route a ship is going to take (when knowing its destination) and also estimate the travel time based on the estimated speed.

When comparing the accuracies of the speed estimates, an ice condition and ship characteristics based algorithm seems to perform better than the simple past-track algorithm, but neither approach is able to cope with the problem of estimating the waiting times if the ship is beset in ice. The past-track algorithm worked reasonably well to predict the route for the ship - this feature could possibly be used in combination with other ways of estimating the speed or risk of getting stuck in an operational route planning tool.

Further research should be done including additional data sources - novel algorithms can be tested on a smallish data sample, before expanding the trials to a larger data set.

10. Acknowledgements

The ice reanalysis data were obtained from the Finnish Meteorological Institute. We are grateful to Jonni Lehtiranta and Mikko Lensu for providing the datasets.

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Appendices

- Correlation matrices
- Grid maps of the 2013, 2014 and 2016 data in 0.1 x 0.2 degree gridcells

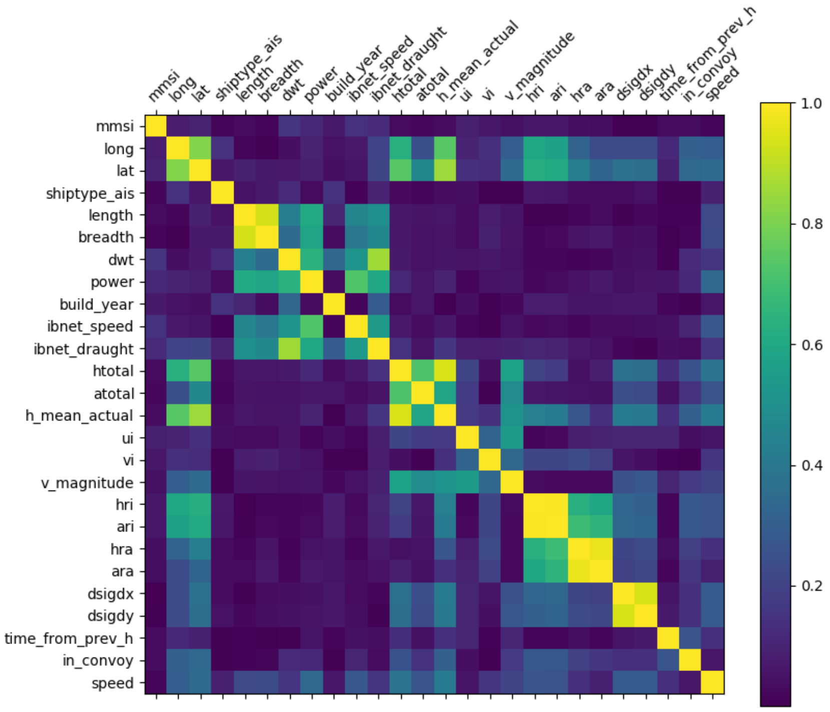

Figure 1 Correlation matrix for 2013 data showing the magnitude of the correlation coefficient describing the extent of a linear relationship between the parameters

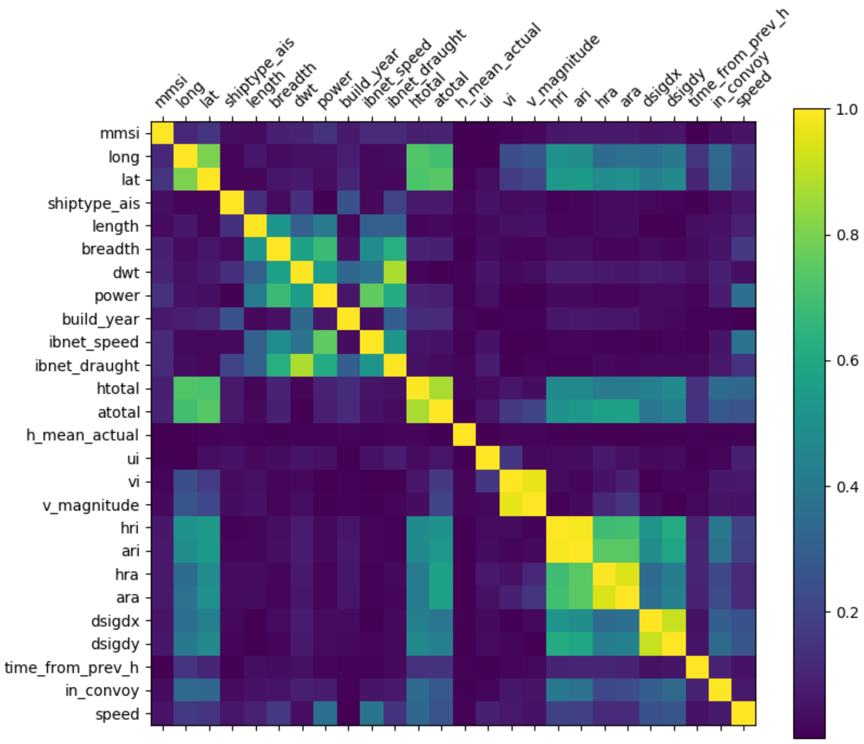

Figure 2 Correlation matrix for 2014 data showing the magnitude of the correlation coefficient describing the extent of a linear relationship between the parameters

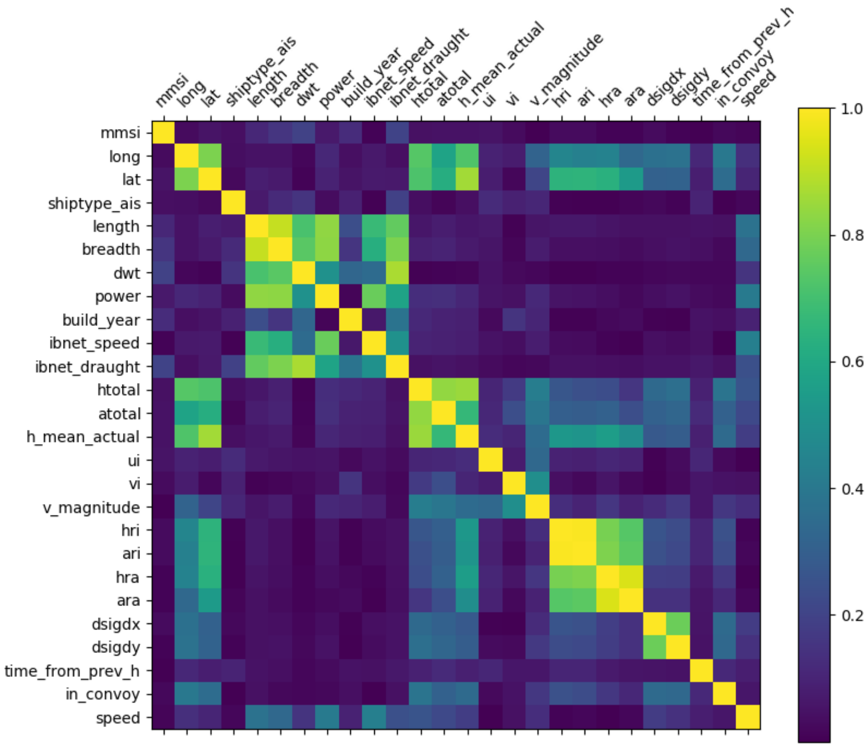

Figure 3 Correlation matrix for 2016 data showing the magnitude of the correlation coefficient describing the extent of a linear relationship between the parameters

2013

Previous ship less than 1 h in same cell

	16.0	16.2	16.4	16.6	16.8	17.0	17.2	17.4	17.6	17.8	18.0	18.2	18.4	18.6	18.8	19.0	19.2	19.4	19.6	19.8	20.0	20.2	20.4	20.6	20.8
66.0																									
65.9																									
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64.2																									
64.1																									
64.0																									
63.9																									
63.8																									
63.7																							21		
63.6																							37		82
63.5																								179	153
63.4																							88	228	
63.3															6		9	11				66	186	7	11
63.2															4	57	12	2	4		44	62	64		
63.1															5	17	12	6		16	26	98	27		
63.0																22		1	6	29	4	86	10		
62.9														2	2	18		3	10	15	2	62	6		
62.8														5	7	6	4	2	12		9	40	6		
62.7												1		5	3	14	10	5	13	2	41	7	5		
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62.5											18		7	2	6	7	3	6	2	15	20		6		
62.4								23	28	44	14	12	8	3			6			17	12	4	6		
62.3								6	38		19	5					18			24	5		6		
62.2											19						2			26	1	3	3		
62.1											13	5					1		2	17		7			9
62.0											13	1					4		5	18		6			6
61.9											8								16	7	6			1	
61.8																	1		13		6				
61.7																	3		13	3	3				
61.6							27	14										5	8	6					
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61.4													5				2	7	3	24	37				4
61.3							6	5									2	13		49	50		1	6	5
61.2							17	3									11	16					4		
61.1															1	2	19	13				1	4	2	6
61.0														2	2	6	33	2	1				3	8	8
60.9													3		1	5	33	2				9	8		11
60.8													3			13	40			4	12	1			22
60.7							12	56	59	6	1				1	38	31	3	5	4		5	1		1
60.6													1	4		66	14	11	4						
60.5																54	12								
60.4																									
60.3																									
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60.1																									
60.0																									

	21.0	21.2	21.4	21.6	21.8	22.0	22.2	22.4	22.6	22.8	23.0	23.2	23.4	23.6	23.8	24.0	24.2	24.4	24.6	24.8	25.0	25.2	25.4	25.6	25.8
66.0																									
65.9																									
65.8																									
65.7																	80		11						
65.6							4										3	144	4						
65.5							36	192	4								26	77							
65.4								33	35	15	19	18	19	13	8	50	40								
65.3								19		32	17	16	16	19	27	25									
65.2				9			6	12	51	5			2	15	19	35	26	26	44						
65.1				28	3		15	30	37					12	11	67	26		13	43	32	29			
65.0					20	5	46	22	2	8					32	30						9	36		
64.9					11	46	32								48	10									
64.8					1	82	7							5	93	9									
64.7		14	14	13	43	136	60	4						31	43	17	6	55							
64.6			4		27	26	89	69	4				6	53	84	121	142	16							
64.5					56	9	6	88	121	82	73	110	94	141	49										
64.4					46			88	56			17	35	7											
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64.1			6	42		136	55		17	61	9														
64.0		2	33		136	149	50	60	109	190	25														
63.9		26		13	213	4		23	46		138														
63.8		25		291	53	47	80	66	1																
63.7	6	56	292	191	52	47	80	40	42																
63.6	280	311	4																						
63.5																									
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63.2	36																								
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63.0																									
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62.2	13																								
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62.0	1																								
61.9																									
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61.5	15	17																							
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61.3																									
61.2																									
61.1	21	119	67																						
61.0	11																								
60.9	1																								
60.8		21	5																						
60.7	78	17																							
60.6	8	5																							
60.5	25	5																							
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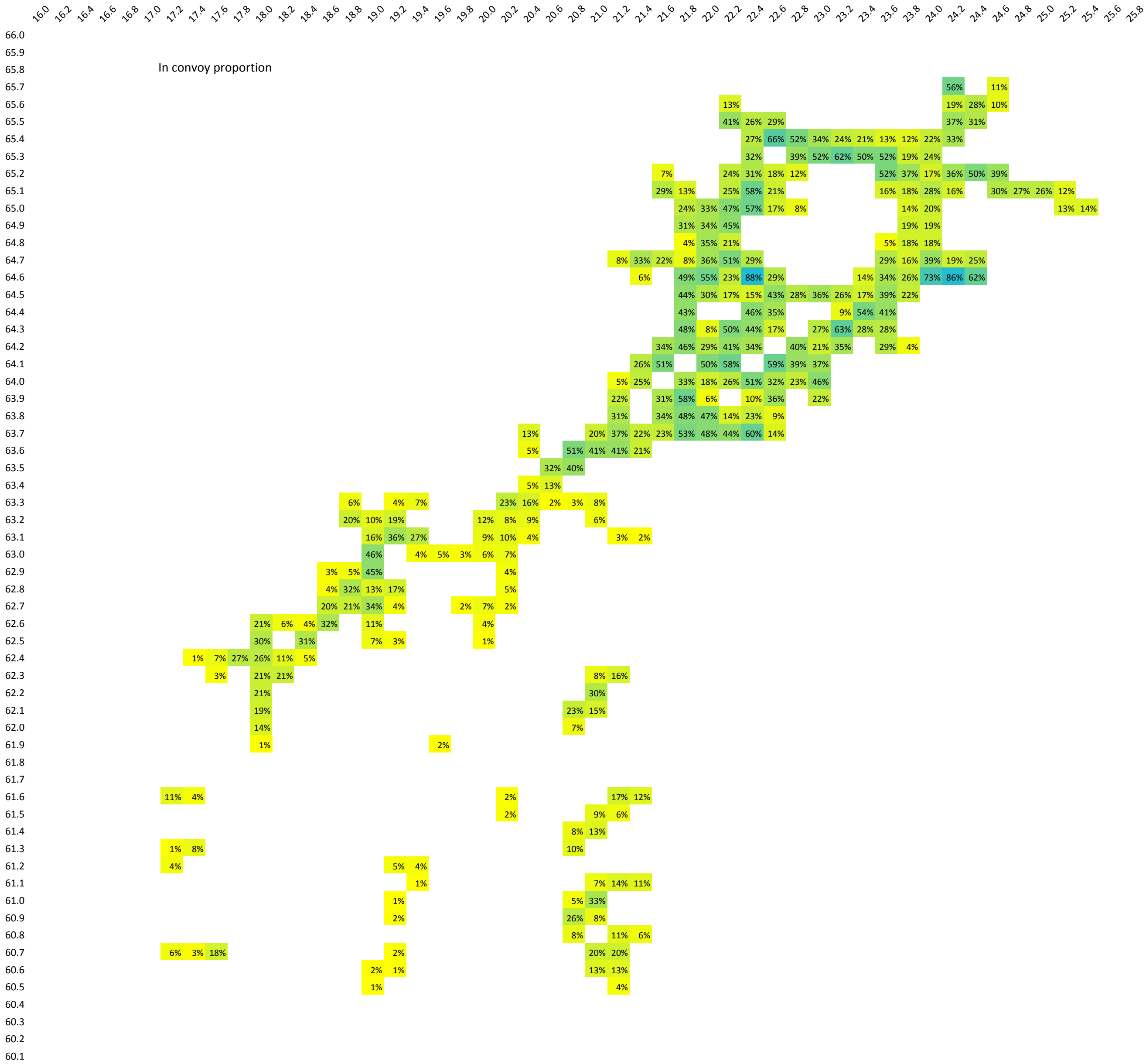
Previous ship less than 1h ago in same gridcell

2013



in convoy proportion

2013

In convoy

	16.0	16.2	16.4	16.6	16.8	17.0	17.2	17.4	17.6	17.8	18.0	18.2	18.4	18.6	18.8	19.0	19.2	19.4	19.6	19.8	20.0	20.2	20.4	20.6	20.8	21.0	21.2	21.4	21.6	21.8	22.0	22.2	22.4	22.6	22.8	23.0	23.2	23.4	23.6	23.8	24.0	24.2	24.4	24.6	24.8	25.0	25.2	25.4	25.6	25.8
66.0																																																		
65.9																																																		
65.8																																																		
65.7																																										67		3						
65.6																																2										3	102	2						
65.5																																21	108	4								18	56							
65.4																																	23	35	14	13	9	7	4	4	37	30								
65.3																																	18		31	16	16	13	16	10	21									
65.2																													6			6	11	26	4				13	14	32	21	25	28						
65.1																													22	3		13	25	14					5	7	44	8		9	20	15	13			
65.0																														19	5	41	20	2	4					17	20						4	9		
64.9																														10	35	23								31	8									
64.8																														1	87	7							1	43	4									
64.7																											2	10	13	14	84	57	4						19	17	11	3	29							
64.6																												1		21	21	50	70	4				3	33	55	101	139	16							
64.5																														36	6	4	51	85	52	55	70	79	126	29										
64.4																														34			66	39			11	30	7											
64.3																														30	1	31	78	3		18	36	19	21											
64.2																													10	21	7	107	12		28	29	6		6	1										
64.1																												5	35		100	45		16	37	7														
64.0																											1	17		77	132	47	53	71	78	16														
63.9																											15		9	178	2		7	30		91														
63.8																											18		207	44	36	22	42	1																
63.7																							9			4	41	168	115	41	36	57	32	10																
63.6																							10		66	191	231	3																						
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63.2															3	21	10				16	21	26			9																								
63.1																15	12	7			7	23	5				3	2																						
63.0																21		1	3	3	2	17																												
62.9														1	2	18						11																												
62.8														2	8	4	4					9																												
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62.6											5	3	1	7		8					7																													
62.5											16		8			3	2				1																													
62.4								1	7	30	12	6	2																																					
62.3									6		15	5														1	8																							
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62.0											12														3																									
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60.9																	4								11	1																								
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60.6																7	2									5	4																							
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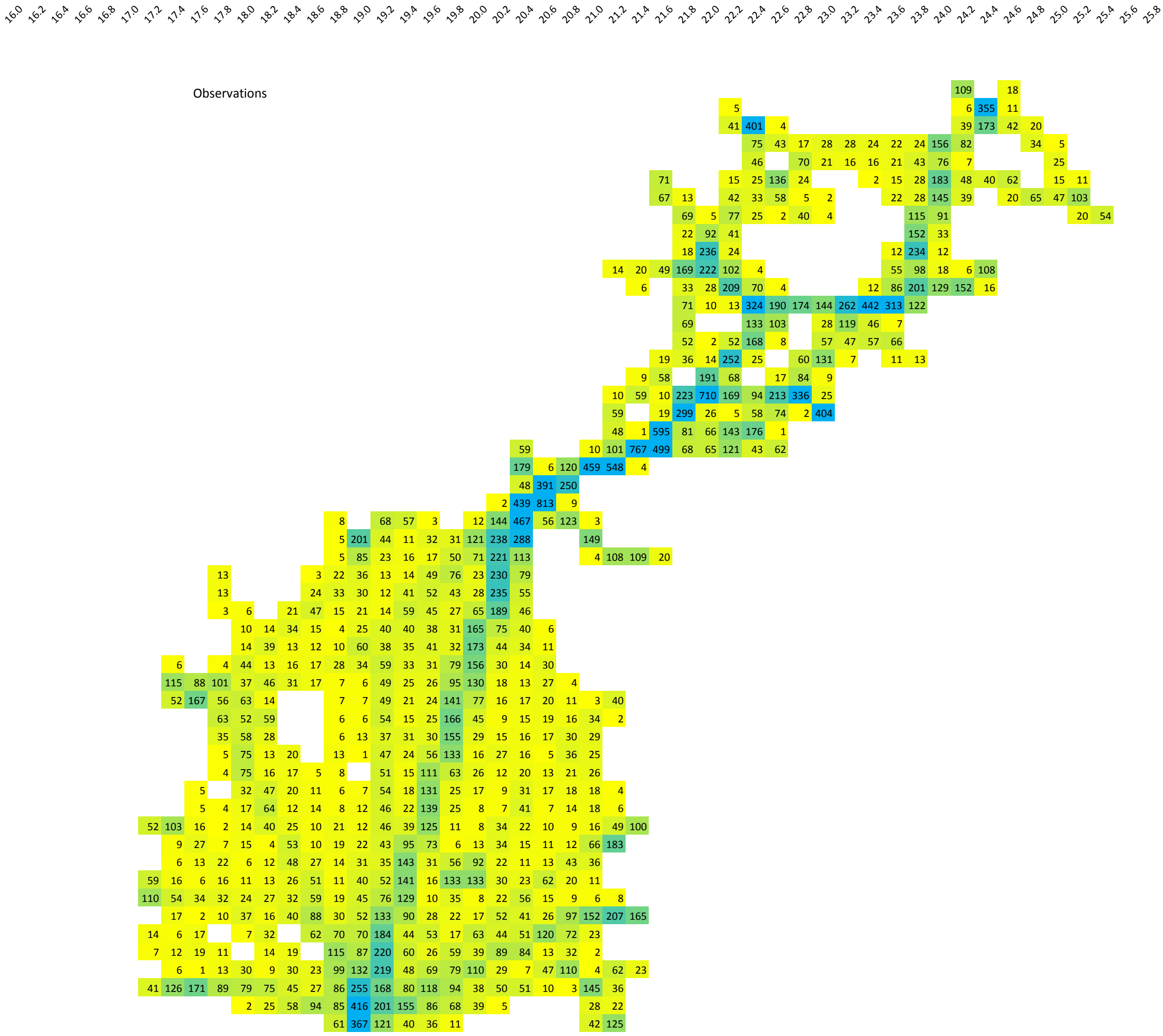
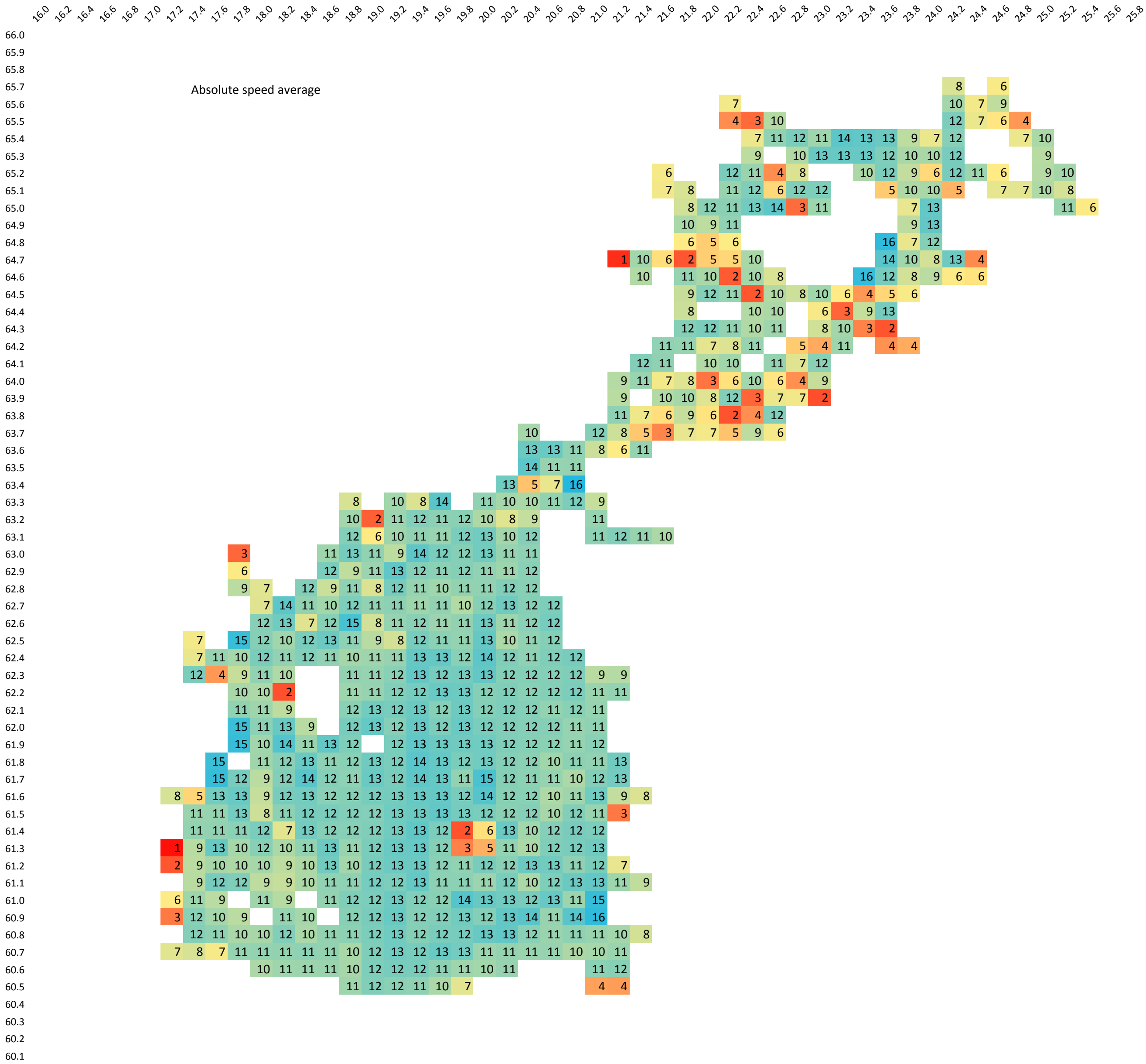
in convoy

2013



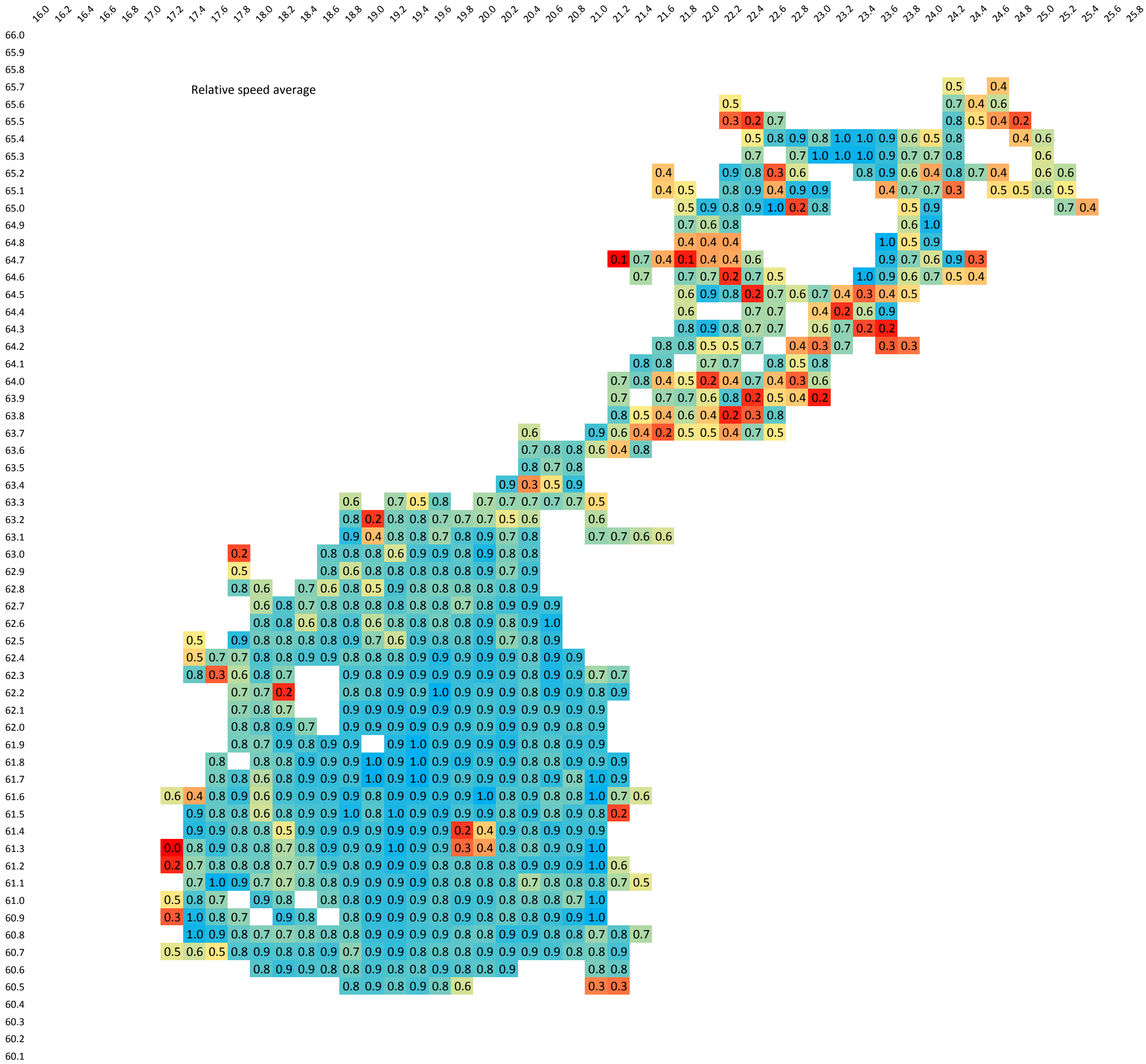
Observations

2013



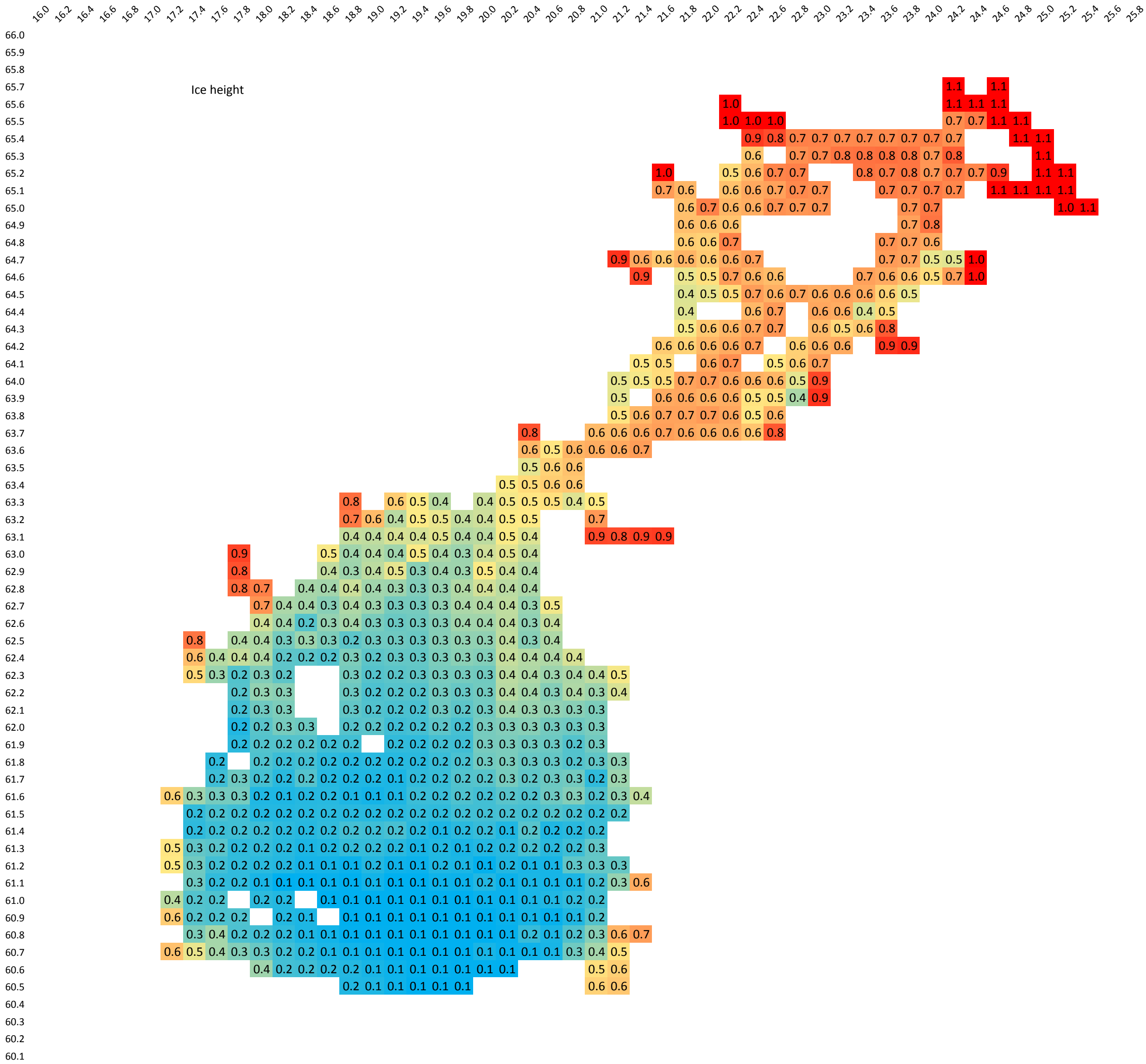
Absolute speed average

2013



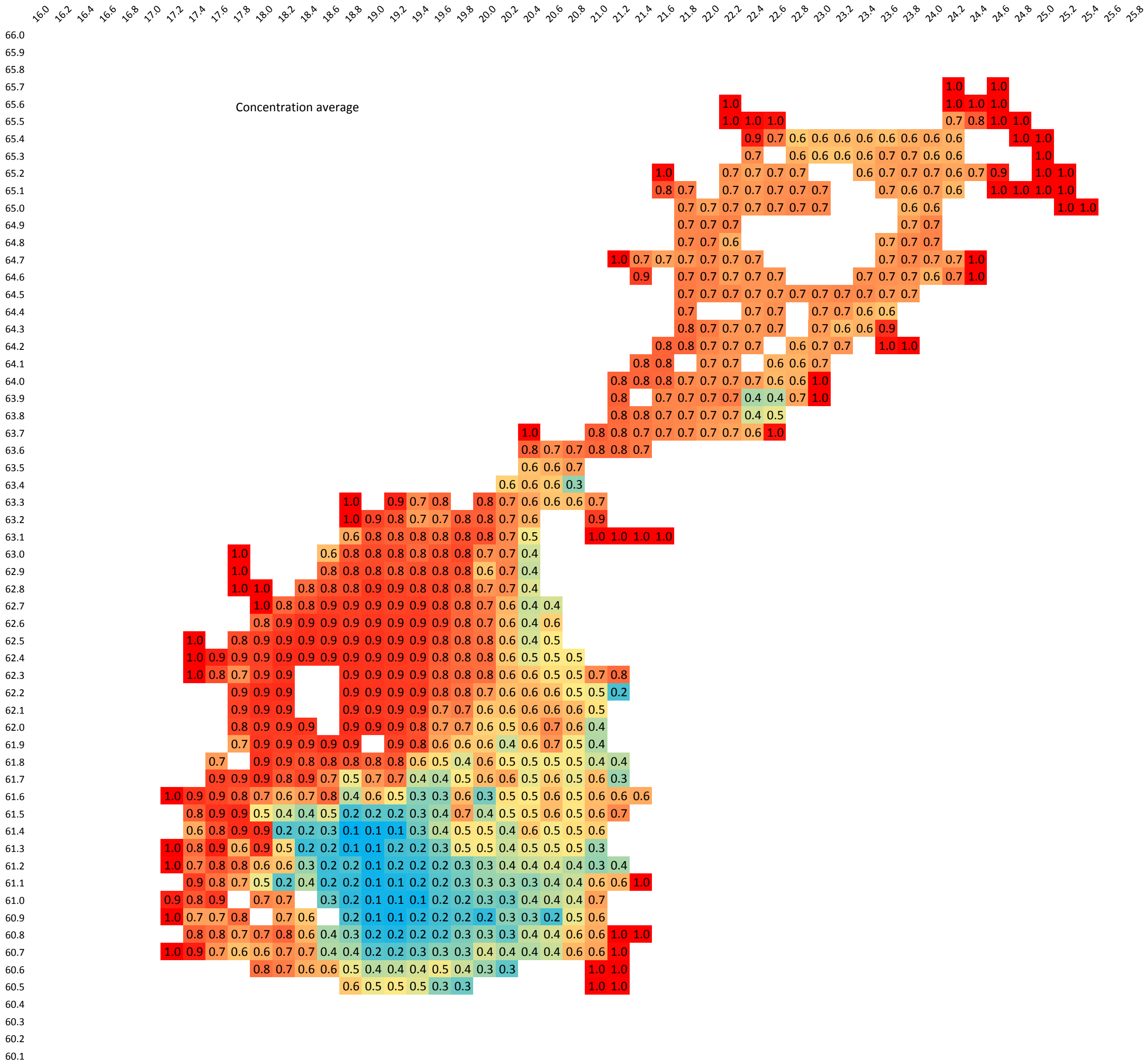
relative speed average

2013



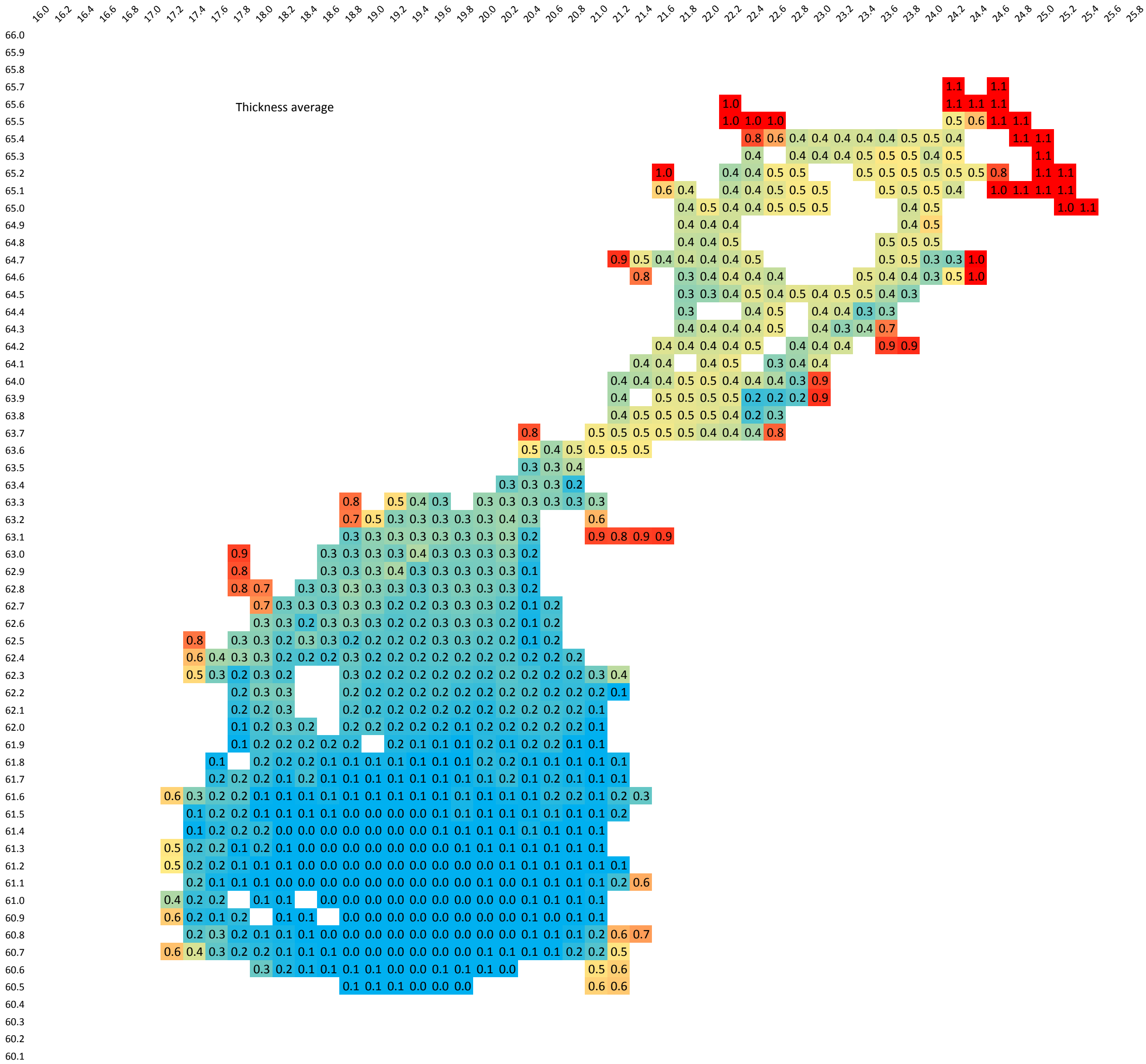
Ice height

2013

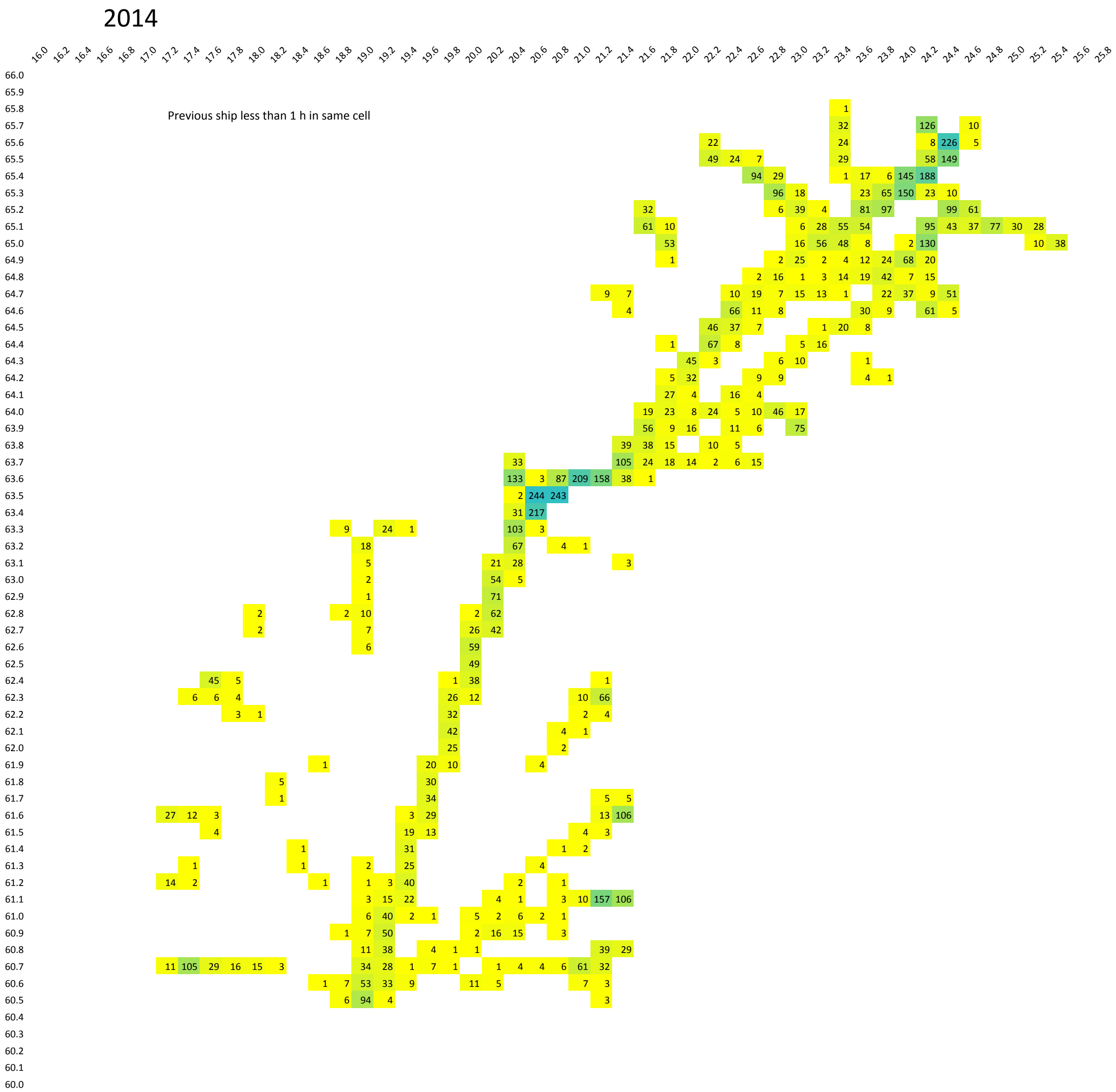


Concentration average

2013

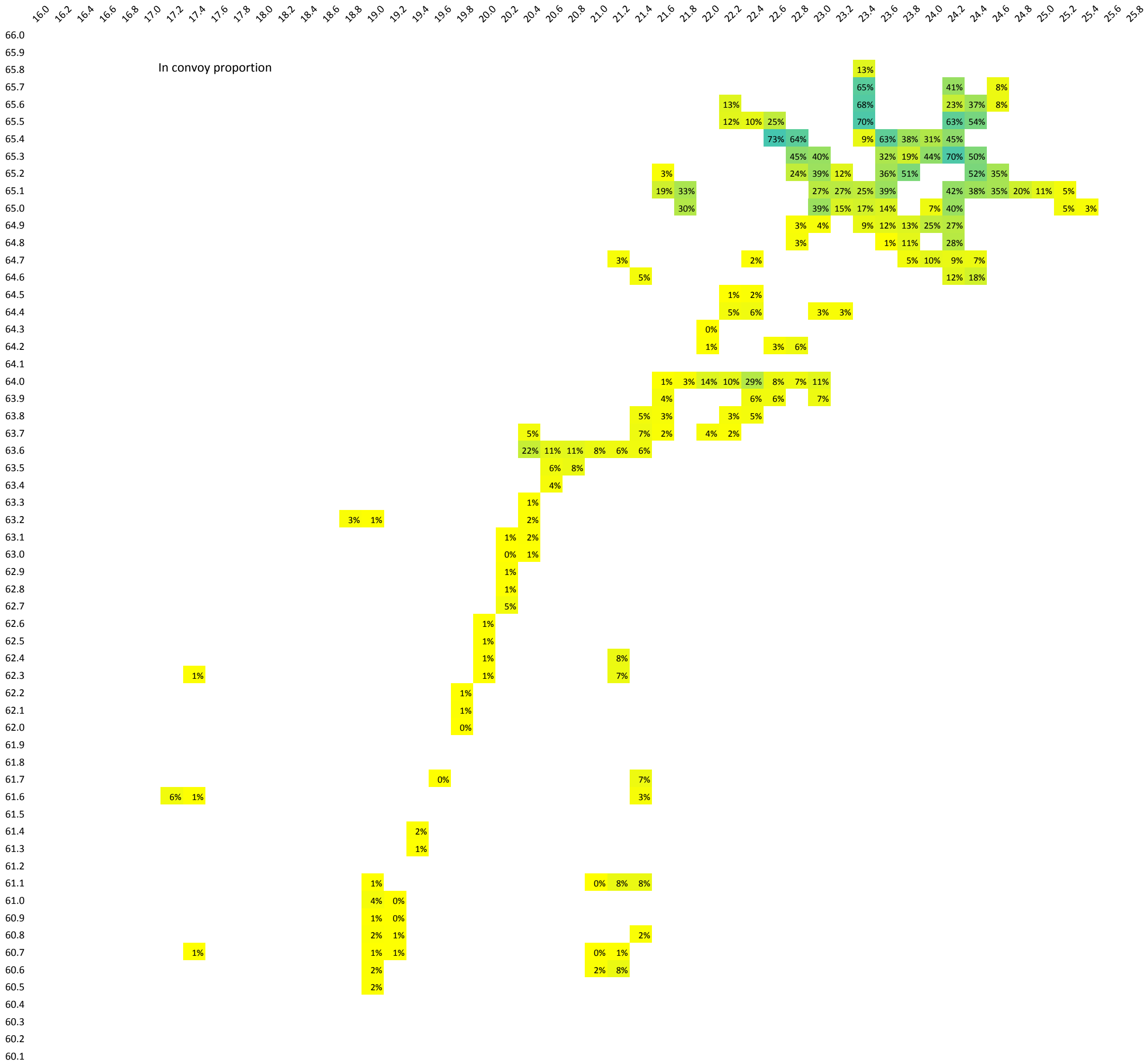


Thickness average



Previous ship in same gridcell less than 1h ago

2014



In convoy proportion

2014

In convoy

	16.0	16.2	16.4	16.6	16.8	17.0	17.2	17.4	17.6	17.8	18.0	18.2	18.4	18.6	18.8	19.0	19.2	19.4	19.6	19.8	20.0	20.2	20.4	20.6	20.8	21.0	21.2	21.4	21.6	21.8	22.0	22.2	22.4	22.6	22.8	23.0	23.2	23.4	23.6	23.8	24.0	24.2	24.4	24.6	24.8	25.0	25.2	25.4	25.6	25.8
66.0																																																		
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65.8																																					3												
65.7																																					28				81		2						
65.6																															8						23				5	157	3						
65.5																															9	16	5				28				49	114							
65.4																																	96	29			1	17	6	86	130								
65.3																																		89	17			19	32	93	23	10							
65.2																												5						6	38	4		55	83			78	43						
65.1																												35	8						6	26	45	47			74	29	25	39	18	8			
65.0																													36						11	30	28	6		1	88					3	3		
64.9																																		1	5		3	11	16	45	13								
64.8																																		4				2	23		13								
64.7																										1						2							5	20	5	8							
64.6																											1														16	4							
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64.0																												2	5	5	10	5	7	9	4														
63.9																												14				6	3		10														
63.8																											12	6			4	2																	
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63.6																						56	2	27	43	33	11																						
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61.0															6	1																																	
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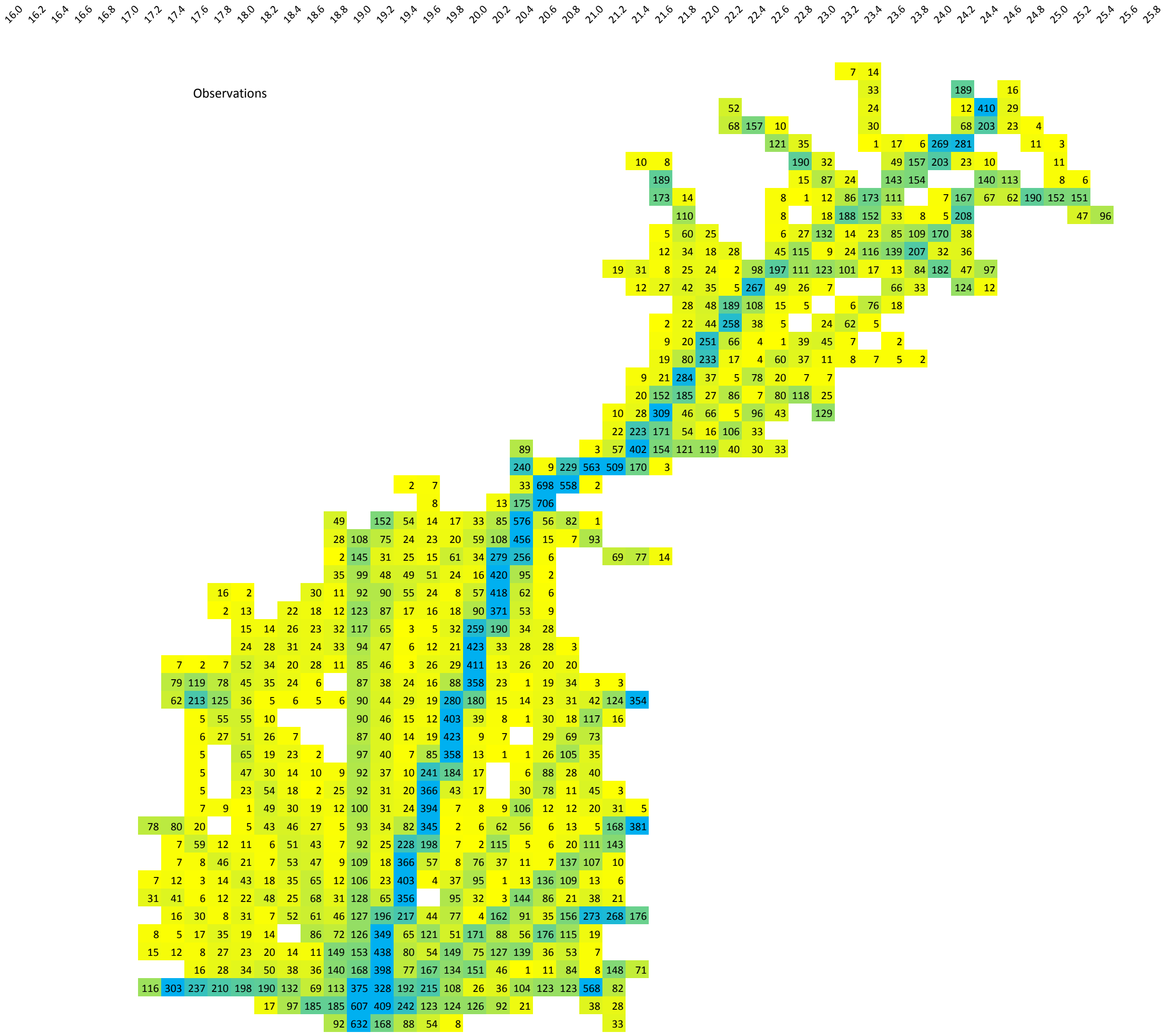
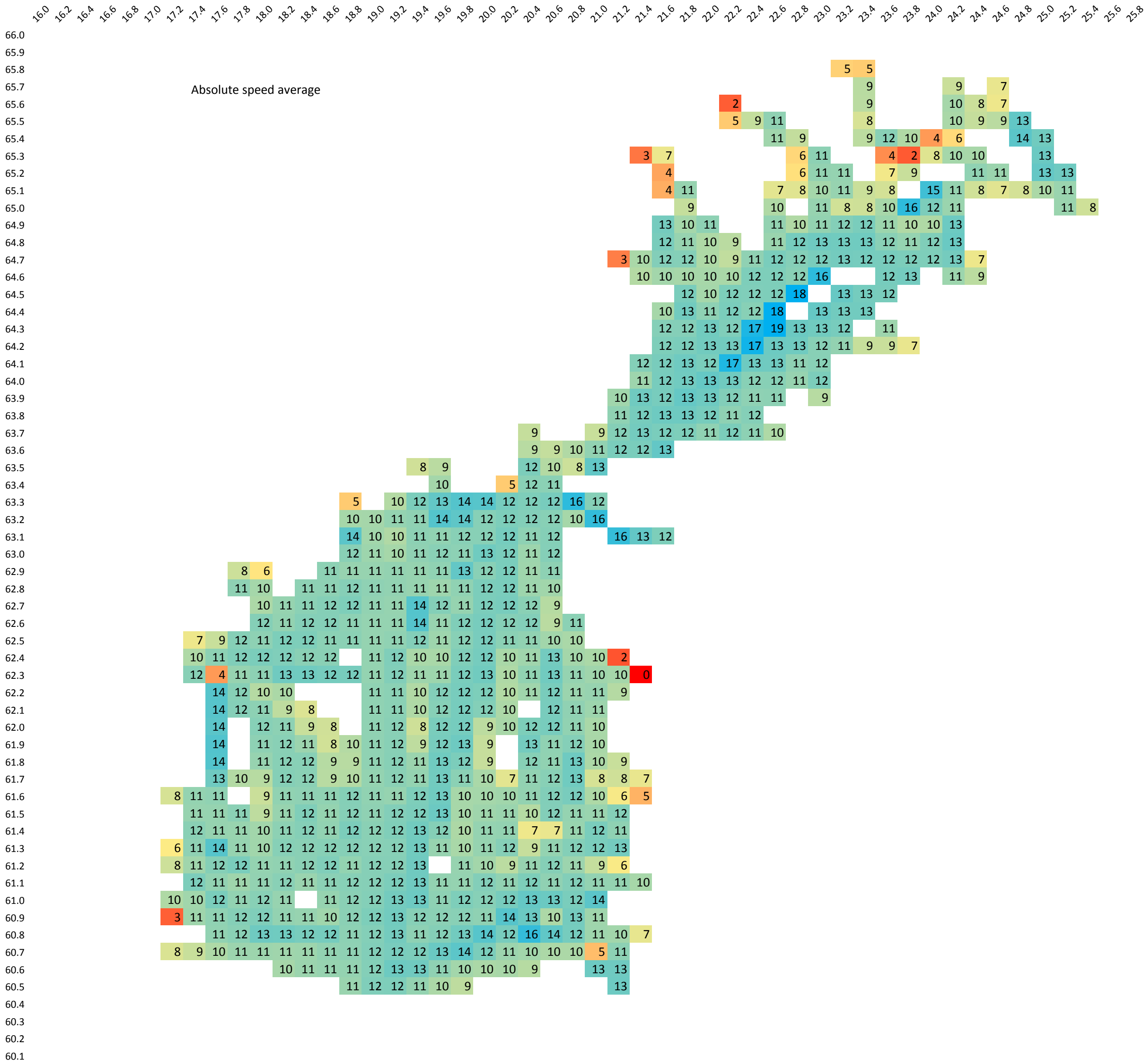
in convoy

2014



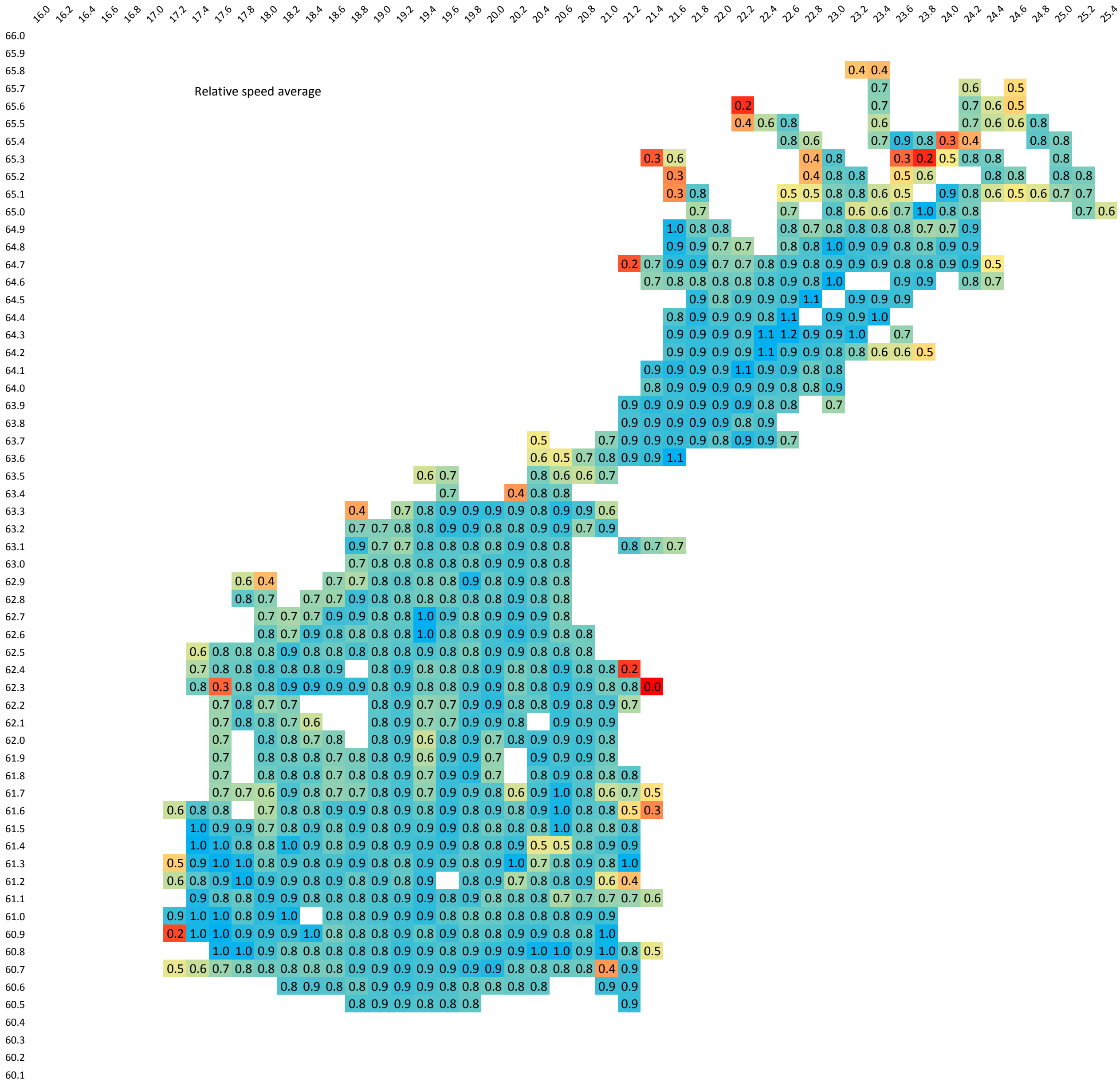
Observations

2014



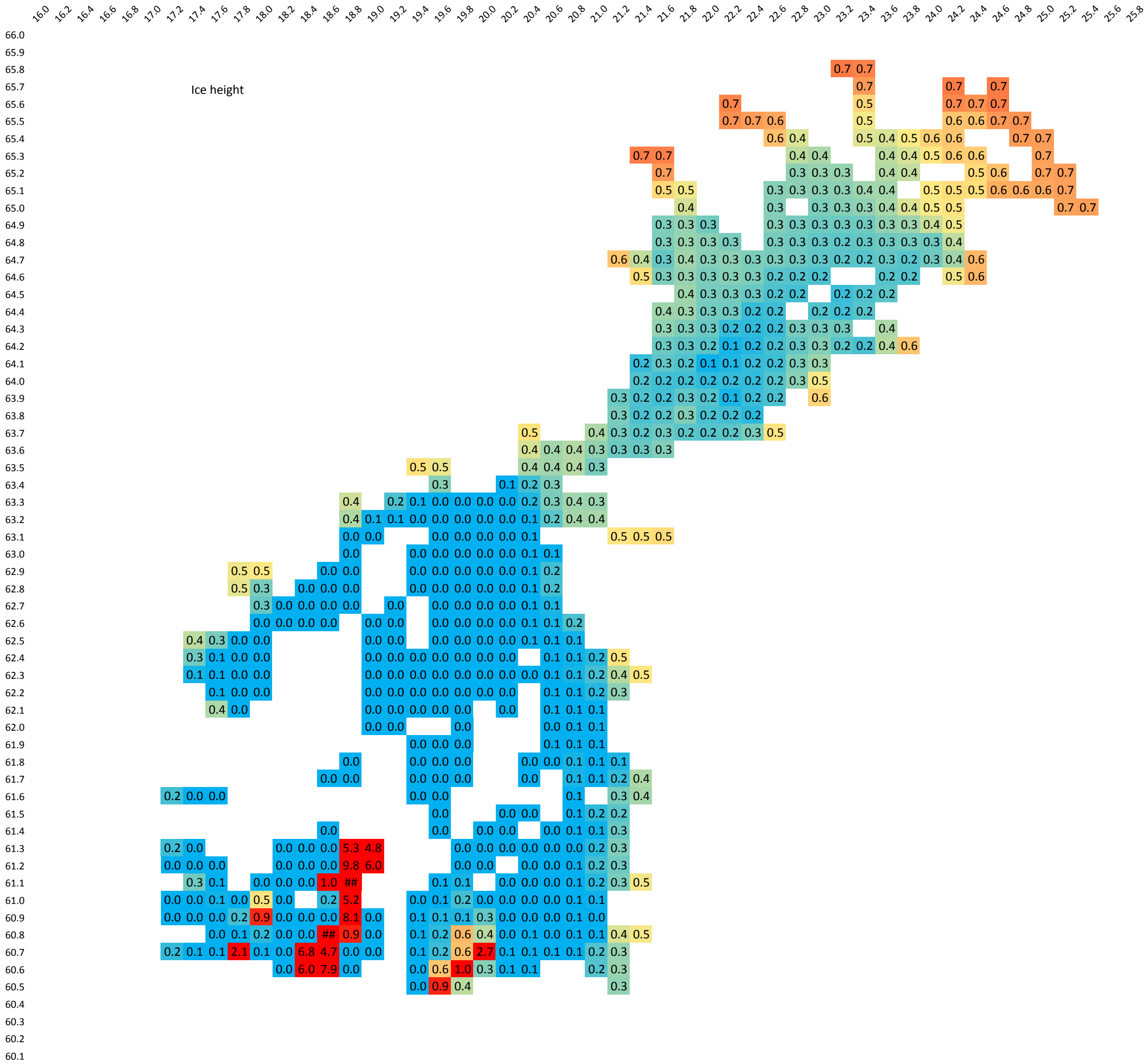
Absolute speed average

2014



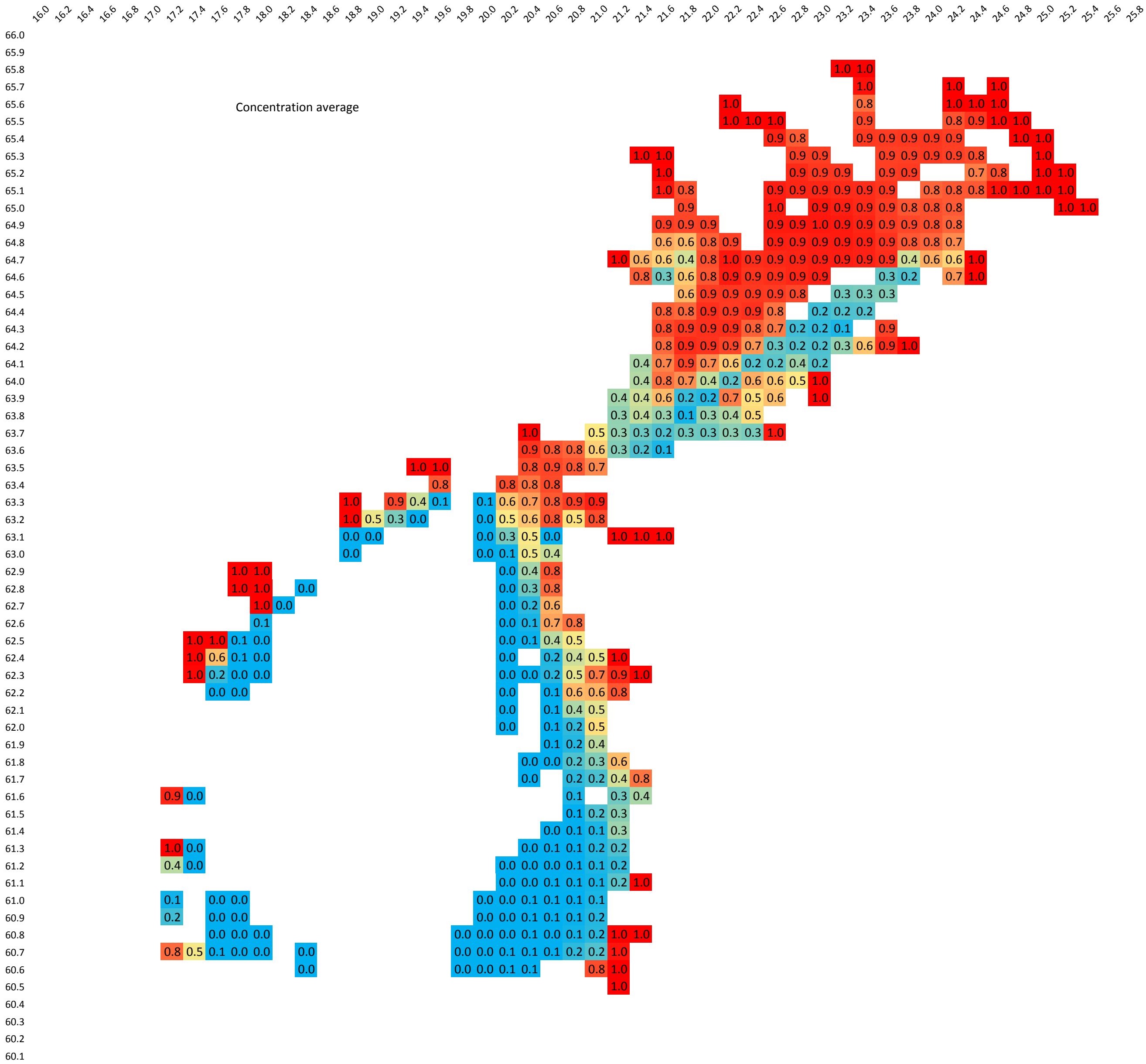
Relative speed average

2014



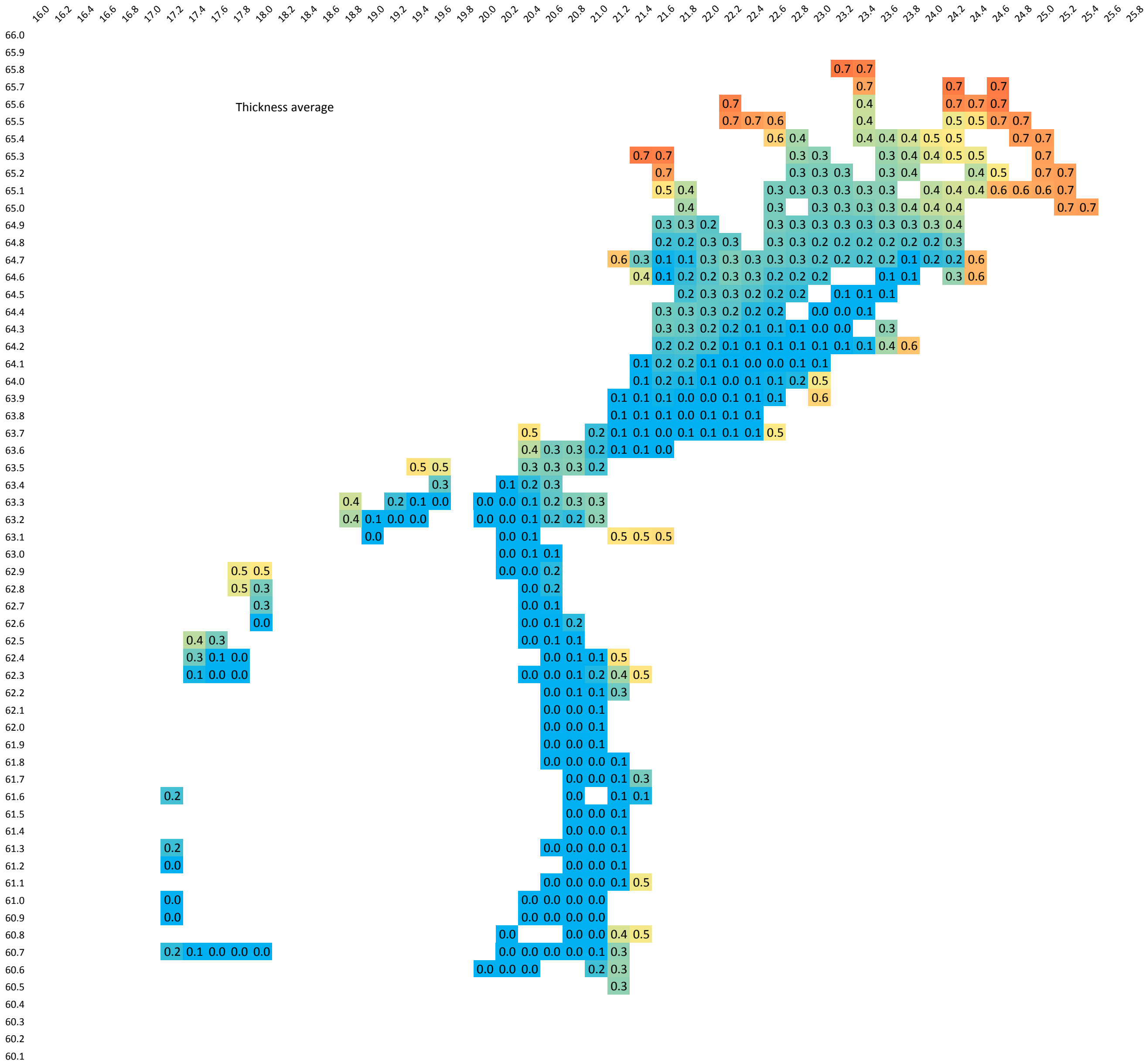
Ice height

2014



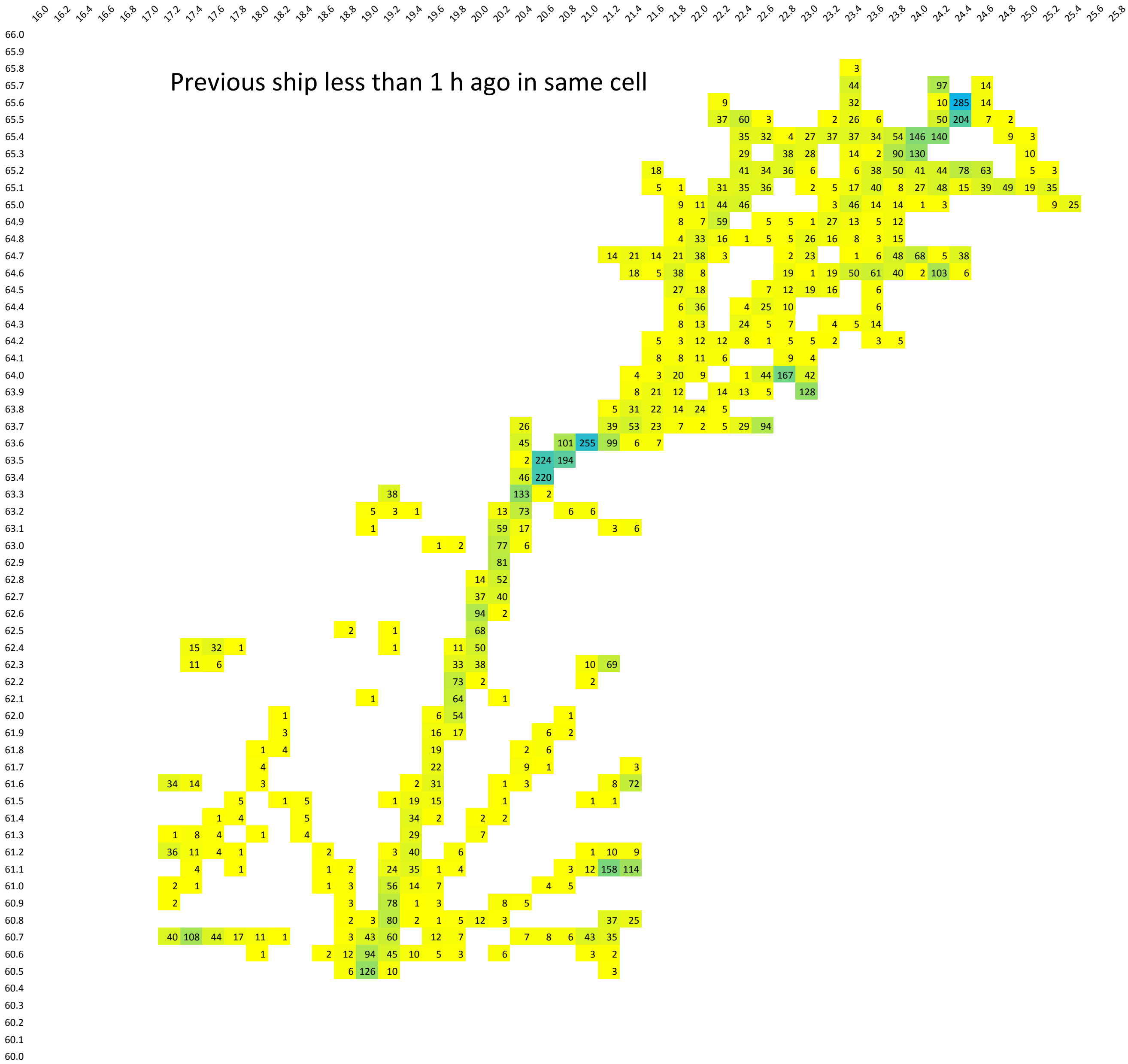
Concentration average

2014

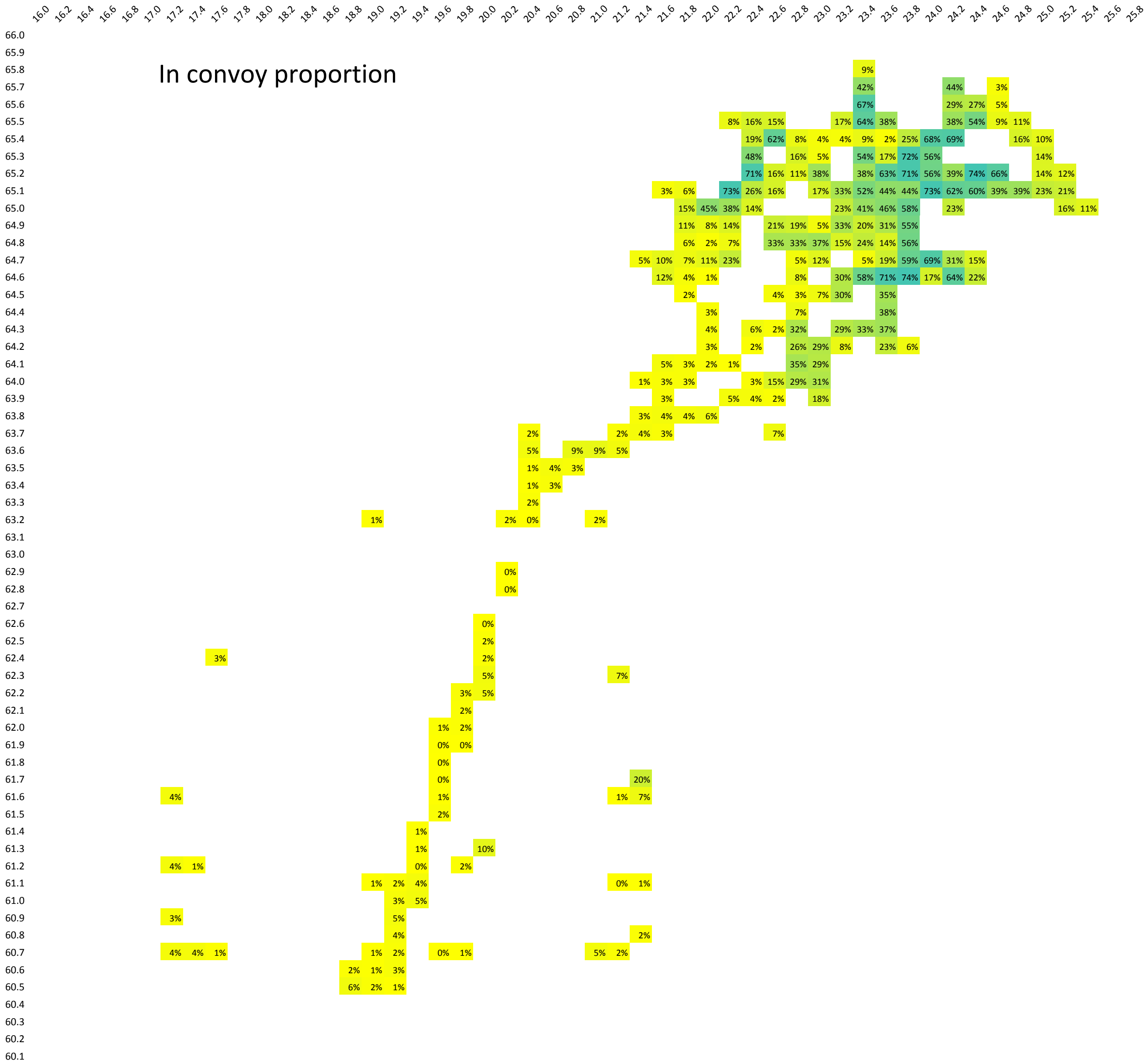


Thickness average

2 0 1 6



2 0 1 6



2 0 1 6

In convoy

	16.0	16.2	16.4	16.6	16.8	17.0	17.2	17.4	17.6	17.8	18.0	18.2	18.4	18.6	18.8	19.0	19.2	19.4	19.6	19.8	20.0	20.2	20.4	20.6	20.8	21.0	21.2	21.4	21.6	21.8	22.0	22.2	22.4	22.6	22.8	23.0	23.2	23.4	23.6	23.8	24.0	24.2	24.4	24.6	24.8	25.0	25.2	25.4	25.6	25.8
66.0																																																		
65.9																																																		
65.8																																						2												
65.7																																						36				81		1						
65.6																																						29				7	167	3						
65.5																																4	16	2			2	23	6			40	165	7	2					
65.4																																	14	26	2	4	5	12	3	37	134	127			7	2				
65.3																																	23		18	5		13	2	83	93					7				
65.2																																	36	16	12	6		6	36	45	31	36	67	53		5	3			
65.1																													2	1		30	25	19		2	5	17	34	8	27	36	15	22	34	20	29			
65.0																														8	10	35	19				3	42	13	14		3					7	9		
64.9																														6	3	26		5	5	1	26	11	5	12										
64.8																														3	4	5		5	5	19	13	7	3	15										
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64.6																													5	8	1				6		18	48	60	40	2	92	4							
64.5																														3				2	4	9	16		6											
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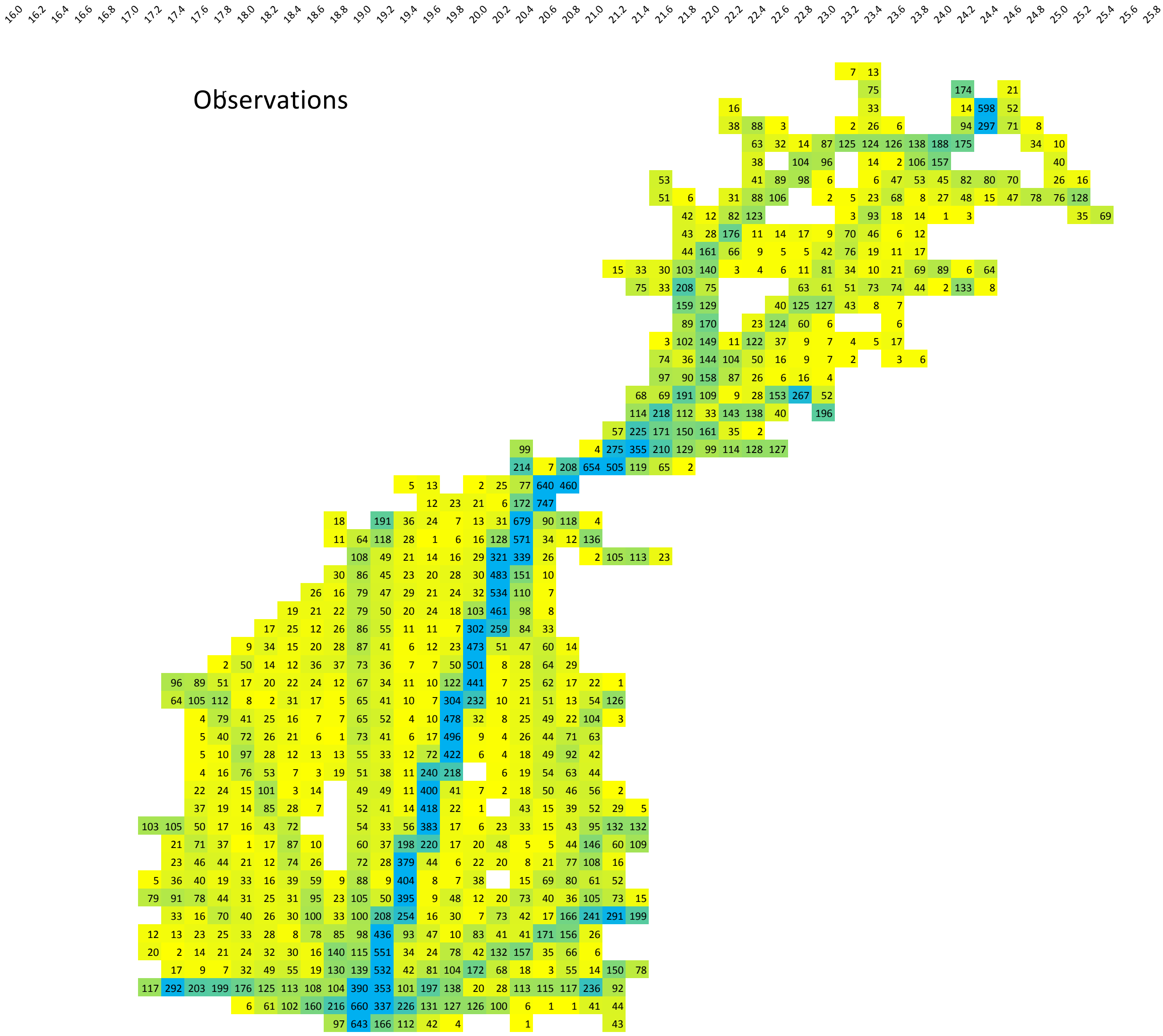
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Observations

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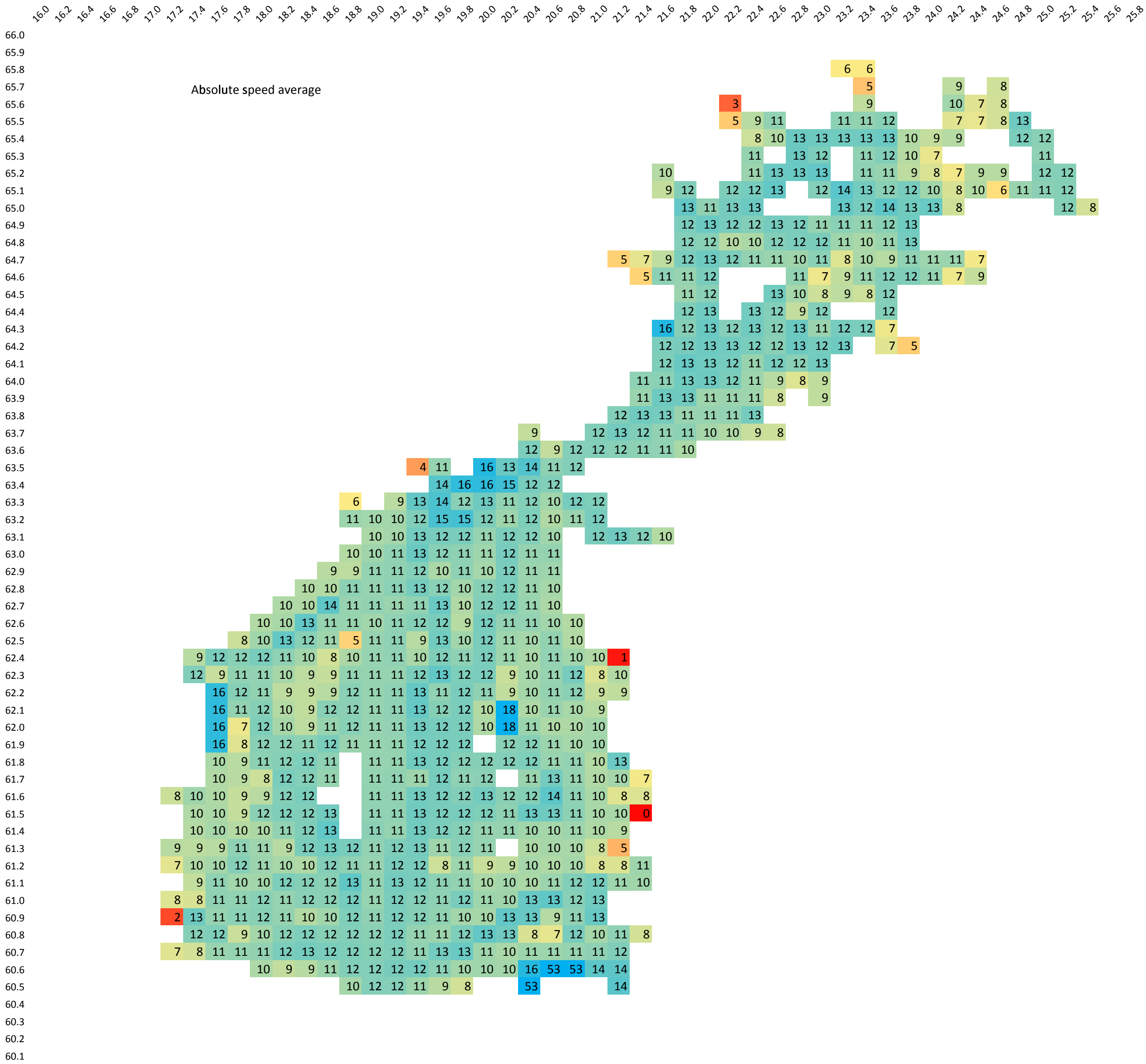

Absolute speed average

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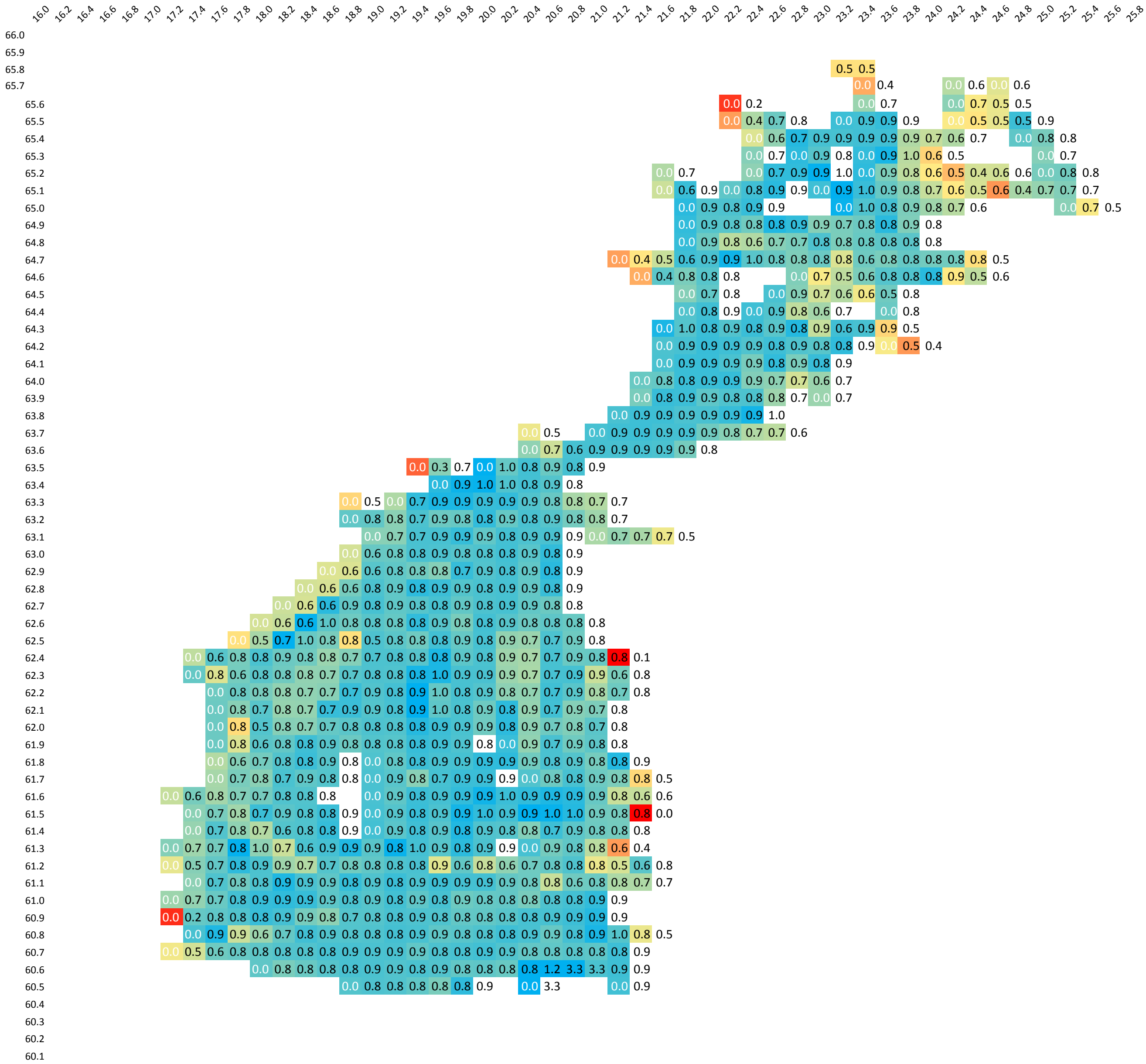

Relative speed average

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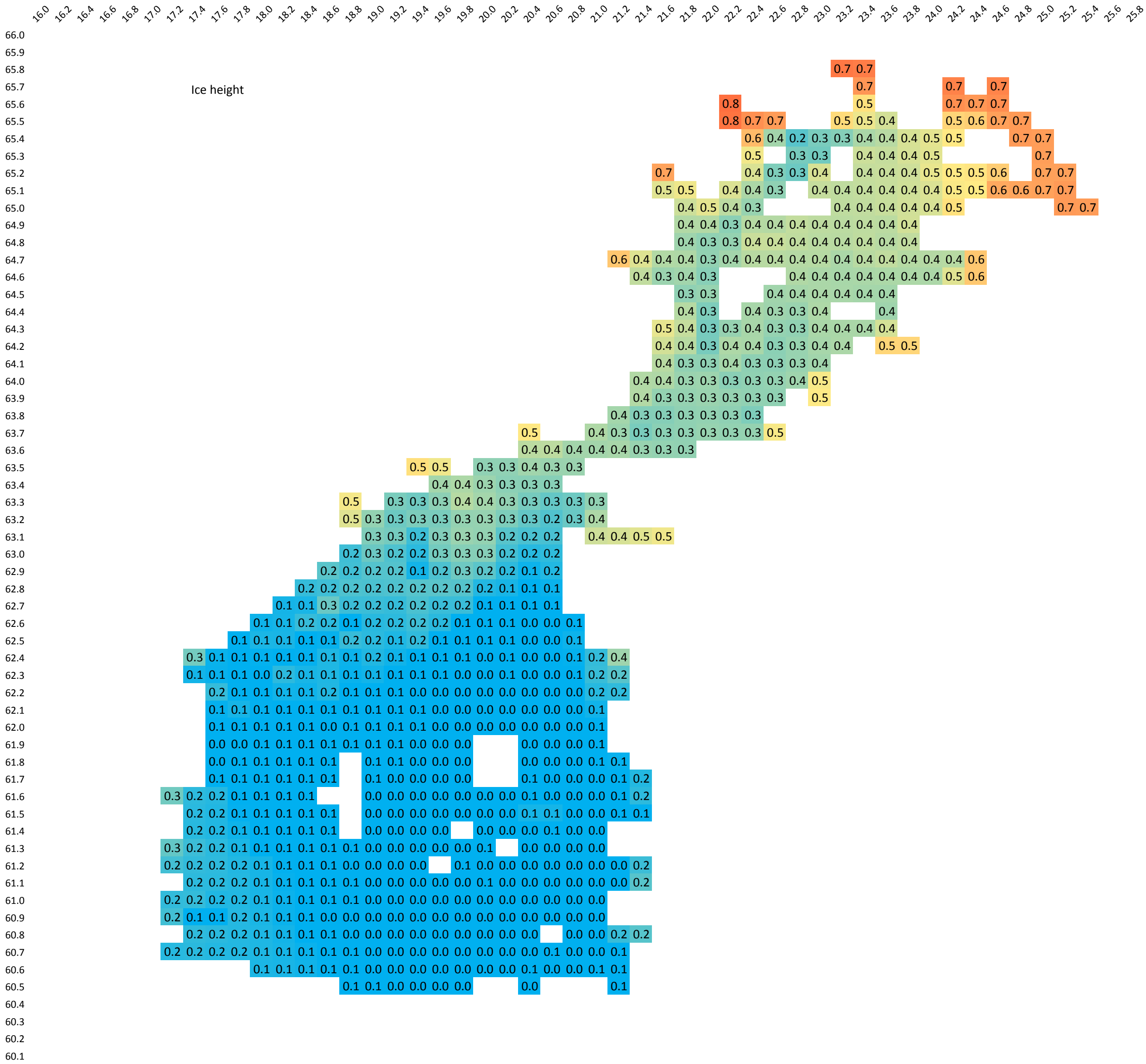
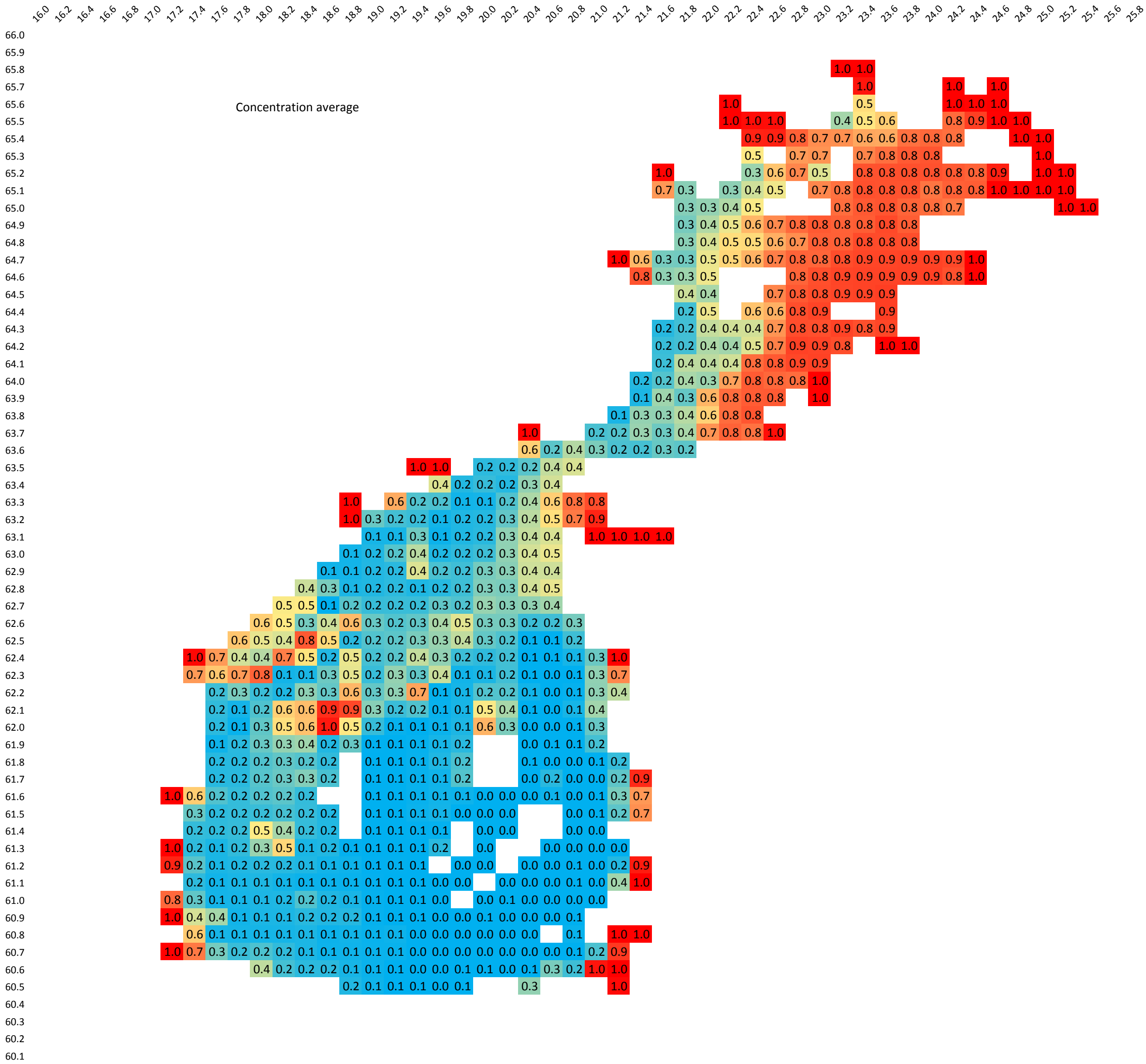


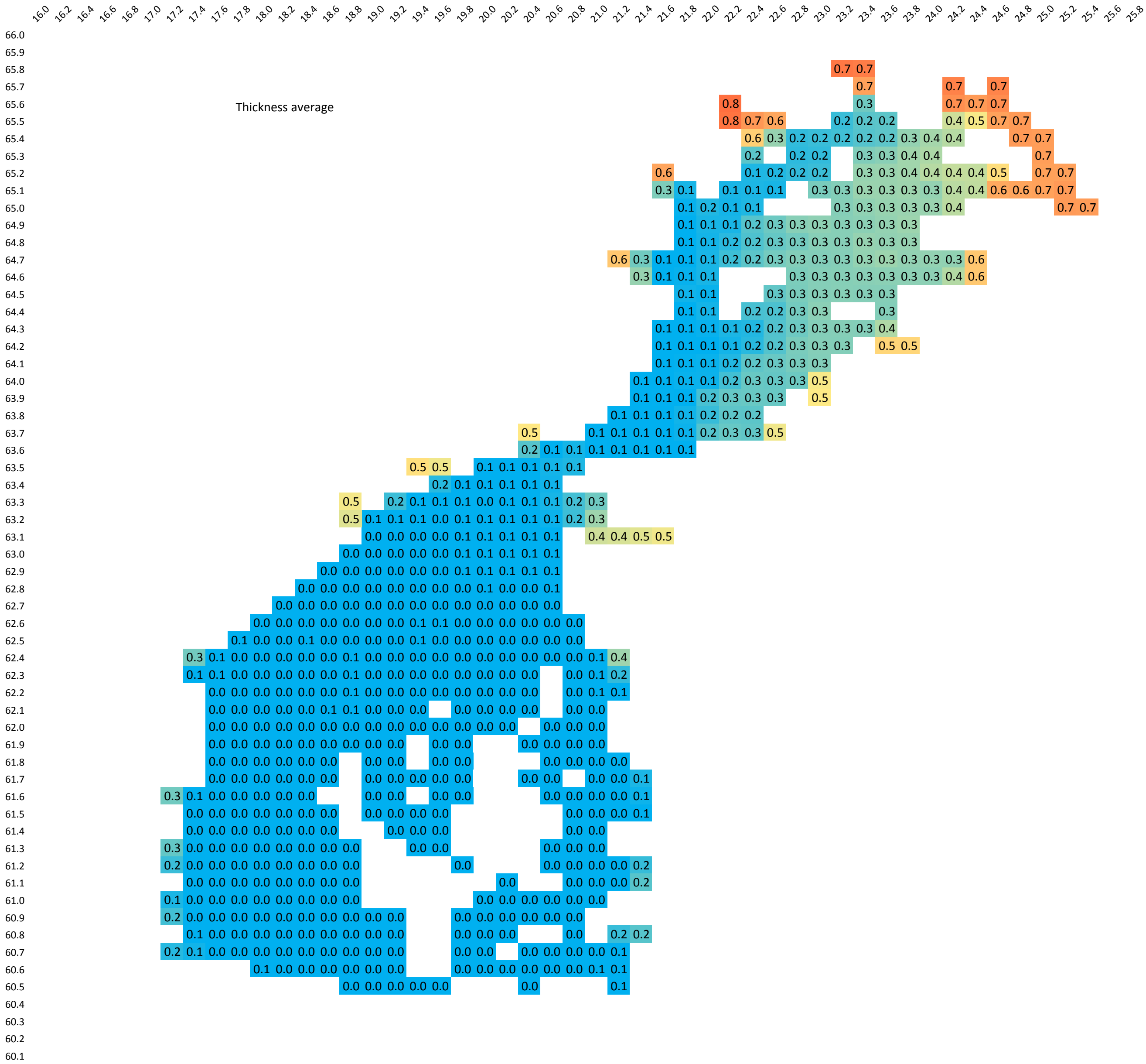
Ice height

2 0 1 6



Concentration average

2 0 1 6



Thickness average