# Exploring Trends in Marine Vessel Automatic Identification System (AIS) disabling events

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# Abstract

The ocean is a vital resource supporting global food supplies and economic activity. Automatic Identification System (AIS) data is a key tool for monitoring vessel activity, and preventing ship collisions at sea. (Windward, "Mind the AIS Gap") Disabling AIS—resulting in "AIS gaps" raises concerns about potential illegal fishing. This study explores whether AIS gaps are primarily used to mask illegal activity or to conceal highly productive fishing locations from competitors. Using a dataset of AIS gaps from Global Fishing Watch, this study analyzes patterns in AIS disabling events, focusing on vessel types, spatial distributions, and the frequency of such events. By examining these dynamics, the study aims to provide insights into the motivations behind AIS disabling, and its importance for global marine conservation.

# Introduction

The ocean is a global resource, providing food, and livelihoods for millions worldwide. As marine resources face increasing pressure from overfishing, technological tools like the Automatic Identification System (AIS) have become indispensable for monitoring and managing vessel activity. AIS is designed to enhance maritime safety by broadcasting vessel positions, but disabling AIS creates data gaps that complicate oversight and raise concerns about illegal fishing activities.

# Methods (data source and wrangling):

This data set was gathered from: global fishing watch. [https://globalfishingwatch.org/data-download/datasets/public-welch-et-al-disabling-events:v20221102](https://globalfishingwatch.org/data-download/datasets/public-welch-et-al-disabling-events:v20221102)

In [21]:
```
pip install pandas
```

```
Requirement already satisfied: pandas in /opt/conda/envs/csm-2024-fall/lib/python3.1
1/site-packages (2.2.2)
Requirement already satisfied: numpy>=1.23.2 in /opt/conda/envs/csm-2024-fall/lib/py
thon3.11/site-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/envs/csm-2024-fa
ll/lib/python3.11/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/envs/csm-2024-fall/lib/pyt
hon3.11/site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /opt/conda/envs/csm-2024-fall/lib/p
ython3.11/site-packages (from pandas) (2023.3)
Requirement already satisfied: six>=1.5 in /opt/conda/envs/csm-2024-fall/lib/python
3.11/site-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

This dataset is pretty clean, but lets get you some info about it anyways.

In [22]:

```python
import pandas as pd


df = pd.read_csv('ais_disabling_events.csv')
df.describe()
```

Out[22]:

| | mmsi | vessel_length_m | vessel_tonnage_gt | gap_start_lat | gap_start_lon | gap_ |
|---|---|---|---|---|---|---|
| **count** | 5.536800e+04 | 55365.000000 | 55368.000000 | 55368.000000 | 55368.000000 | |
| **mean** | 4.150034e+08 | 53.113900 | 857.755972 | 0.207077 | 10.602479 | |
| **std** | 1.206791e+08 | 21.321896 | 711.376427 | 31.963962 | 116.896361 | |
| **min** | 6.120000e+02 | 10.620000 | 12.000000 | -76.095333 | -179.983000 | |
| **25%** | 4.120563e+08 | 36.520000 | 276.000000 | -19.853636 | -79.861616 | |
| **50%** | 4.124999e+08 | 54.999773 | 736.000000 | -2.366897 | -16.121833 | |
| **75%** | 4.167720e+08 | 69.900000 | 1269.000000 | 26.938788 | 152.517194 | |
| **max** | 9.997636e+08 | 255.390000 | 9499.000000 | 78.214127 | 179.993508 | |

In [23]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55368 entries, 0 to 55367
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   gap_id                        55368 non-null  object
 1   mmsi                          55368 non-null  int64
 2   vessel_class                  55368 non-null  object
 3   flag                          54666 non-null  object
 4   vessel_length_m               55365 non-null  float64
 5   vessel_tonnage_gt             55368 non-null  float64
 6   gap_start_timestamp           55368 non-null  object
 7   gap_start_lat                 55368 non-null  float64
 8   gap_start_lon                 55368 non-null  float64
 9   gap_start_distance_from_shore_m  55368 non-null  float64
 10  gap_end_timestamp             55368 non-null  object
 11  gap_end_lat                   55368 non-null  float64
 12  gap_end_lon                   55368 non-null  float64
 13  gap_end_distance_from_shore_m  55368 non-null  float64
 14  gap_hours                     55368 non-null  float64
dtypes: float64(9), int64(1), object(5)
memory usage: 6.3+ MB
```

This schema is listed on the global fishing watch wesbite: https://globalfishingwatch.org/data-download/datasets/public-welch-et-al-disabling-events:v20221102

Schema

The ais_disabling_events.csv file contains the following fields:

```
gap_id: Unique id of the AIS disabling event
mmsi: Maritime Mobile Service Identity (MMSI) number of the vessel.
MMSI is the unique identifier in AIS data.
vessel_class: Geartype of the vessel. Grouped into five categories
- trawlers, drifting longlines, squid jiggers, tuna purse seines,
and other.
flag: Flag state (ISO3) of the vessel.
vessel_length_m: Vessel length (meters)
vessel_tonnage_gt: Vessel tonnage (gross tons)
gap_start_timestamp: Time (UTC) at the start of the AIS disabling
event
gap_start_lat: Latitude of the vessel at the start of the AIS
disabling event
gap_start_lon: Longitude of the vessel at the start of the AIS
disabling event
gap_start_distance_from_shore_m: Distance from shore (meters) of
the vessel at the start of the AIS disabling event
gap_end_timestamp: Time (UTC) at the end of the AIS disabling event
gap_end_lat: Latitude of the vessel at the end of the AIS disabling
event
gap_end_lon: Longitude of the vessel at the end of the AIS
disabling event
gap_end_distance_from_shore_m: Distance from shore (meters) of the
```

```
vessel at the end of the AIS disabling event
gap_hours: Duration (hours) of the AIS disabling event.
```

(Global Fishing Watch, Public Welch et al. Disabling Events Dataset: v20221102)

Their github is here: https://github.com/GlobalFishingWatch/AIS-disabling-high-seas/tree/v1.0.0

# Results (viz and stats)

In [3]:
```
pip install geopy
```

```
Collecting geopy
  Using cached geopy-2.4.1-py3-none-any.whl.metadata (6.8 kB)
Collecting geographiclib<3,>=1.52 (from geopy)
  Using cached geographiclib-2.0-py3-none-any.whl.metadata (1.4 kB)
Using cached geopy-2.4.1-py3-none-any.whl (125 kB)
Using cached geographiclib-2.0-py3-none-any.whl (40 kB)
Installing collected packages: geographiclib, geopy
Successfully installed geographiclib-2.0 geopy-2.4.1
Note: you may need to restart the kernel to use updated packages.
```

In [18]:
```
from geopy.distance import geodesic

#calculate total gap hours and number of records per vessel
vessel_gap_summary = df.groupby('mmsi')['gap_hours'].sum().reset_index()
vessel_gap_summary.rename(columns={'gap_hours': 'total_gap_hours'}, inplace=True)
print(vessel_gap_summary.head())# Group by vessel class and calculate the total and
vessel_class_summary = df.groupby('vessel_class')['gap_hours'].agg(['sum', 'mean',
vessel_class_summary.rename(columns={
    'sum': 'total_gap_hours',
    'mean': 'average_gap_hours',
    'count': 'number_of_gaps'
}, inplace=True)

# Sort by total gap hours to see which vessel types turn off AIS most
vessel_class_summary.sort_values('total_gap_hours', ascending=False, inplace=True)

print(vessel_class_summary)
```

```
     mmsi  total_gap_hours
0     612        31.016667
1     732        21.883333
2     857        17.683333
3   92455        24.383333
4  201851      3556.766667
        vessel_class  total_gap_hours  average_gap_hours  number_of_gaps
0  drifting_longlines     2.201604e+06         118.105483           18641
4    tuna_purse_seines     1.241893e+06         144.071098            8620
2        squid_jigger     9.952089e+05          62.119028           16021
3            trawlers     6.195127e+05          78.290499            7913
1               other     5.002938e+05         119.888286            4173
```

In [5]:
```
# Identify unique vessels with at least one gap per class
vessels_with_gaps = df.groupby('vessel_class')['mmsi'].nunique().reset_index()
vessels_with_gaps.rename(columns={'mmsi': 'vessels_with_gaps'}, inplace=True)

# Count the total number of unique vessels per class
total_vessels = df.groupby('vessel_class')['mmsi'].nunique().reset_index()
total_vessels.rename(columns={'mmsi': 'unique_vessels'}, inplace=True)

# Merge the two datasets
vessel_class_summary = vessels_with_gaps.merge(total_vessels, on='vessel_class')

# Calculate the percentage of vessels with gaps
vessel_class_summary['percent_with_gaps'] = (
    vessel_class_summary['vessels_with_gaps'] / vessel_class_summary['unique_vessel
)

# Display the corrected summary
print(vessel_class_summary)
```

```
        vessel_class  vessels_with_gaps  unique_vessels  percent_with_gaps
0  drifting_longlines               2191            2191              100.0
1               other                945             945              100.0
2        squid_jigger                806             806              100.0
3            trawlers                917             917              100.0
4    tuna_purse_seines               419             419              100.0
```

Every vessel in this study has a gap. so that's interesting I may need to learn more about the input data source, or if the way it's collected a gap would be expected. But either way, Let's move into a heat map to see the locations where the gaps are lat/long wise.

In [17]:
```
import numpy as np

#create bins 10 degree in both direction
lat_bins = np.arange(-90, 91, 10)
lon_bins = np.arange(-180, 181, 10)

# Bin latitude and longitude into regions
df['lat_bin'] = pd.cut(df['gap_start_lat'], bins=lat_bins, labels=lat_bins[:-1])
df['lon_bin'] = pd.cut(df['gap_start_lon'], bins=lon_bins, labels=lon_bins[:-1])

# group by regions
regional_gaps = df.groupby(['lat_bin', 'lon_bin']).agg(
    total_gap_hours=('gap_hours', 'sum'),
    average_gap_hours=('gap_hours', 'mean'),
    total_distance_from_shore_km=('gap_start_distance_from_shore_m', sum)
).reset_index()

# Sort regions by total gap hours
regional_gaps = regional_gaps.sort_values(by='total_gap_hours', ascending=False)

# Display the top regions
print(regional_gaps.head(10))
```

```
    lat_bin lon_bin  total_gap_hours  average_gap_hours  \
155     -50     -70    544003.216667          82.349866
501      40     150    226553.583333          53.019795
502      40     160    166257.783333          55.697750
311     -10      50    138900.333333         228.079365
156     -50     -60    136870.133333          78.300992
323     -10     170    120306.633333         116.126094
341       0     -10    111028.166667         172.136693
289     -10    -170    104020.816667         189.128758
322     -10     160    102178.083333         115.065409
340       0     -20    100434.683333         141.457300

     total_distance_from_shore_km
155                  2.512077e+09
501                  2.328716e+09
502                  2.417102e+09
311                  1.509340e+08
156                  6.841650e+08
323                  2.513240e+08
341                  2.015690e+08
289                  2.470570e+08
322                  2.492310e+08
340                  2.962790e+08
```

```
/tmp/ipykernel_504/3920906307.py:12: FutureWarning: The default of observed=False is
deprecated and will be changed to True in a future version of pandas. Pass observed=
False to retain current behavior or observed=True to adopt the future default and si
lence this warning.
  regional_gaps = df.groupby(['lat_bin', 'lon_bin']).agg(
/tmp/ipykernel_504/3920906307.py:12: FutureWarning: The provided callable <built-in
function sum> is currently using SeriesGroupBy.sum. In a future version of pandas, t
he provided callable will be used directly. To keep current behavior pass the string
"sum" instead.
  regional_gaps = df.groupby(['lat_bin', 'lon_bin']).agg(
```

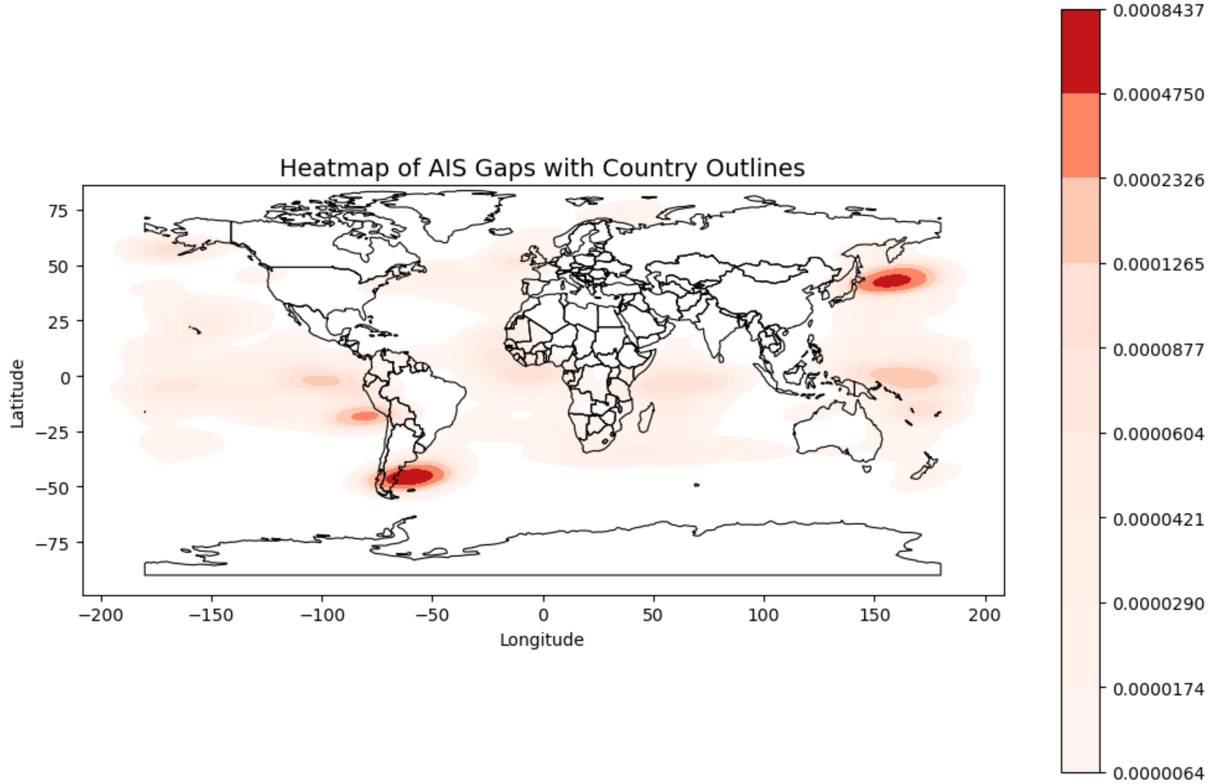
%matplotlib inline

In [7]:

```python
import geopandas as gpd
import matplotlib.pyplot as plt
import seaborn as sns

#Load shapefile from GeoPandas
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Prepare data
gap_locations = df[['gap_start_lat', 'gap_start_lon']].dropna()

# Plot the heatmap
fig, ax = plt.subplots(figsize=(12, 8))
sns.kdeplot(
    x=gap_locations['gap_start_lon'],
    y=gap_locations['gap_start_lat'],
    cmap="Reds",
    fill=True,
    cbar=True,
    bw_adjust=0.5,
    ax=ax
)
```

```
# Plot country borders
world.boundary.plot(ax=ax, color='black', linewidth=0.8)

# Add labels
plt.title('Heatmap of AIS Gaps with Country Outlines', fontsize=14)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

```
/tmp/ipykernel_504/2019904162.py:6: FutureWarning: The geopandas.dataset module is d
eprecated and will be removed in GeoPandas 1.0. You can get the original 'naturalear
th_lowres' data from https://www.naturalearthdata.com/downloads/110m-cultural-vector
s/.
  world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
```




Alright so here's a heat map with countries outlined with AIS gap information. An interesting piece of future data would be to add additional markings for protected areas where fishing is limited or prohibited. If there was a high corellation of AIS gaps near protected areas that may be something to consider. this heat map looks like it has two major hotspots. One is north east of Japan (45, 150) and the other is between Argentina and the falkland islands. (-50, -60)

Now that we have two hot spots I'm interested to see if AIS events are near protected areas.

I imported a dataset from Protected Planet with shapes of protected fishiung areas. to combine with the previous heatmap.

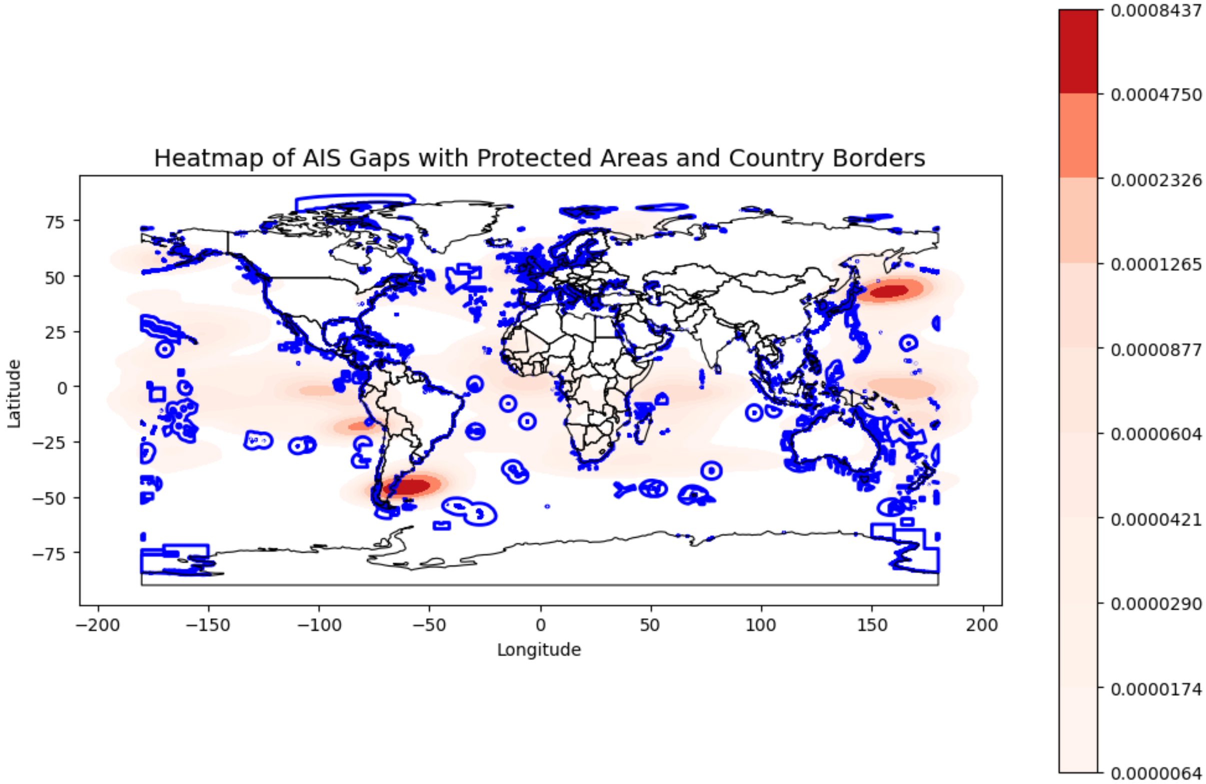
https://www.protectedplanet.net/en/search-areas?filters%5Bis_type%5D%5B%5D=marine (Protected Planet, "Search Areas: Marine")

In [8]:

```
import geopandas as gpd
import seaborn as sns
import matplotlib.pyplot as plt
from shapely.geometry import Point

#load world shapefile
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Load the protected areas data
protected_loc_df = gpd.read_file('WDPAgeodb.gdb', layer='WDPA_WDOECM_poly_Dec2024_1

# Load AIS gap locations (assuming 'gap_start_lat' and 'gap_start_lon' columns are
gap_locations = df[['gap_start_lat', 'gap_start_lon']].dropna()
geometry = [Point(lon, lat) for lon, lat in zip(gap_locations['gap_start_lon'], gap

# Create a GeoDataFrame for AIS gap locations
gdf_gaps = gpd.GeoDataFrame(gap_locations, geometry=geometry)

# Set the coordinate reference system (CRS) to WGS84 (EPSG:4326)
gdf_gaps.crs = 'EPSG:4326'

# Plot the combined map
fig, ax = plt.subplots(figsize=(12, 8))

# Plot the heatmap of AIS gaps
sns.kdeplot(
    x=gdf_gaps.geometry.x,
    y=gdf_gaps.geometry.y,
    cmap="Reds",
    fill=True,
    cbar=True,
    bw_adjust=0.5,
    ax=ax
)

# Plot country borders
world.boundary.plot(ax=ax, color='black', linewidth=0.8)

# Plot the boundaries of protected areas
protected_loc_df.plot(ax=ax, facecolor='none', edgecolor='blue', linewidth=2)

# Title and labels
plt.title('Heatmap of AIS Gaps with Protected Areas and Country Borders', fontsize=
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

```
# Show the plot
plt.show()
```

```
/tmp/ipykernel_504/3944122693.py:7: FutureWarning: The geopandas.dataset module is d
eprecated and will be removed in GeoPandas 1.0. You can get the original 'naturalear
th_lowres' data from https://www.naturalearthdata.com/downloads/110m-cultural-vector
s/.
  world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
```




I'd like to see if there's a corellation between the type of fishing vessel and the heat map, or if certain vessels are more likely to have AIS gaps near protected areas. Either way, based on this heat map, I don't think that the hot spots are particularly close to specific protected areas, however some of these gaps last many hours, and could enable a ship to move to the protected area, and then back out within that window. Future work will include breaking down this heat map by vessel type.

# Discussion (who cares?)

This analysis of AIS disabling events among maritime vessels reveals patterns in the usage of AIS gaps. Certain vessel types may be more prone to AIS disabling and different geographic locations have higher occurrences of AIS gaps. While the motivations for these gaps remain speculative, several hypotheses emerge:

```
Strategic Concealment:
    Patterns of AIS disabling may align with economically
productive fishing areas, supporting the hypothesis that vessels
disable AIS to protect fishing locations from competitors.
```

```
Illegal Activities:
    Conversely, the occurrence of disabling events in regions
associated with illegal fishing activities cannot be discounted.
Spatial correlations with known illegal fishing hotspots would
strengthen this hypothesis. Or a dataset with the ability to check
if a vessel has the correct documentation or licensing to fish in
that region could also help.

Operational Challenges:
    Non-malicious explanations, such as equipment failure due to an
overcrowded area or weather can also account for some AIS gaps.
```

Implications for Conservation Policy: Understanding the motivations behind AIS disabling is vital for informed fisheries management and maritime policy. Enhanced monitoring, combined with targeted enforcement in high-risk areas, could deter illegal activities while respecting legitimate vessels rite to the seas. Further research into spatial-temporal patterns and collaboration with maritime stakeholders can refine these insights.

Future Directions: This study highlights the importance of integrating AIS data with environmental and economic datasets. Investigating correlations between AIS gaps and marine productivity paired with field investigation could provide a clearer picture of vessel behavior. Leveraging machine learning techniques for anomaly detection in AIS data could enhance predictive capabilities for maritime oversight.

# Citations

Global Fishing Watch. "Public Welch et al. Disabling Events Dataset: v20221102." Global Fishing Watch, Global Fishing Watch, 2 Nov. 2022, https://globalfishingwatch.org/data-download/datasets/public-welch-et-al-disabling-events:v20221102. Accessed 3 Dec. 2024.

Global Fishing Watch. AIS Disabling on the High Seas, Version 1.0.0. GitHub, Global Fishing Watch, https://github.com/GlobalFishingWatch/AIS-disabling-high-seas/tree/v1.0.0. Accessed 3 Dec. 2024.

Protected Planet. "Search Areas: Marine." Protected Planet, UN Environment Programme, https://www.protectedplanet.net/en/search-areas?filters%5Bis_type%5D%5B%5D=marine. Accessed 3 Dec. 2024.

Windward. "Mind the AIS Gap." Windward, Windward, 26 Apr. 2023, https://windward.ai/blog/mind-the-ais-gap/.