MAREL Carnot data and metadata from Coriolis Data Center

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Abstract. The French coast of the Eastern English Channel (ECC) is classified as a potential eutrophication zone by the Paris and Oslo Convention (OSPAR) and as moderate to poor according to the phytoplankton quality element of the Water Framework Directive (WFD). It is regularly affected by *Phaeocystis globosa* bloom events, which have detrimental effects on the marine ecosystem, economy, and public health. In this context and to improve our observation strategy, MAREL Carnot, a multi-sensor oceanographic station, was installed in the Eastern English Channel in 2004 at the Carnot wall in Boulogne sur Mer. The aim of this station was to collect high frequency measurements of several water quality parameters to complement conventional low-resolution monitoring programs. The purpose of this paper is to describe the MAREL Carnot dataset and show how it can be used for several research objectives. MAREL Carnot collects high-frequency, multi-parameter observations from surface water as well as meteorological measurements and sends the data in near real-time to an inshore data center. In this paper, we present several physical, chemical, and biological parameters measured by this station. We also demonstrate that the MAREL Carnot dataset can be used to assess environmental or ecological statuses and conduct research in the field of marine phytoplankton ecology, and oceanography. In addition, we show that this dataset may indirectly aid in improving European environmental management strategies.

1 Introduction

For millennia, the marine environment has been subjected to various sources of pollution. Major inputs of nitrate, phosphate, and other pollutants have been causing detrimental effects on the marine environment, including harmful algal blooms (HAB) and eutrophication (Le Moal et al., 2019). Since phytoplankton are at the base of the food web, their blooms can affect higher trophic levels and cause serious changes in marine biodiversity and water quality (e.g., oxygen deficiency) (Kazmi et al., 2022; Young et al., 2020). HABs can produce toxins that degrade water quality and cause health problems in humans and marine animals (Ross Brown et al., 2022; Young et al., 2020). They can also be associated with mass foam accumulations on beaches,

as with *Phaeocystis globosa* blooms (Blauw et al., 2010; Spilmont et al., 2009). Furthermore, they can detrimentally cause economic losses in sectors such as fish farms, shellfish aquaculture, tourism, and recreational activities, as well as public health

35 (Derot et al., 2020; Hallegraeff et al., 2021).

Understanding the processes underlying HABs and eutrophication necessitates continuous monitoring of the marine environment in order to prevent the associated deterioration effects and achieve optimized environmental assessment and management strategies. Traditionally, monitoring aquatic and marine ecosystems was done using low frequency in situ measurements (weekly to monthly sampling frequency). It was performed by collecting water samples through Niskin bottles

40 and then performing several laboratory analyses to determine various physical, chemical, and biological parameters, including salinity, temperature, conductivity, organic and inorganic matter, as well as phytoplankton biomass, abundance and diversity. Despite the fact that these data helped scientists have an overview of the processes taking place in the marine environment, they are of insufficient temporal resolution to advance understanding of phytoplankton dynamics and eutrophication.

In order to implement proper management strategies that prevent further deterioration of the marine ecosystem, it is crucial to

45 enhance our understanding of algal blooms, eutrophication, recurrent, rare, and extreme events, as well as phytoplankton dynamics. Thus, it is necessary to collect continuous measurements not only on a monthly or weekly basis but also on an hourly or even sub hourly scale. Satellites and models can provide data of high spatio-temporal resolution (Chai et al., 2020), but such data must be validated with in situ data (Lefebvre and Schmitt, 2016). This motivated scientists to study the marine environment using in situ high frequency (high temporal resolution) monitoring systems such as buoys, ferry boxes, etc.

50 (Dickey and Bidigare, 2005).

Over the past decades, the advancement of sensor technology and data science has shed light on the importance of time series in marine research. This urged the construction of autonomous systems capable of supporting long-term time series for key physical, chemical, and biological parameters. The implementation of such automated systems enabled the measurement of essential ocean variables (EOV) and essential biodiversity variables (EBV) at high frequency, which aided in reorienting

55 marine research from low frequency measurements to high frequency measurements (Blain et al., 2004).

In the Eastern English Channel (EEC), HABs are mainly caused by the Prymnesiophyceae, *Phaeocystis globosa,* which is often associated with *Pseudo-nitzchia* (Karasiewicz and Lefebvre, 2022). When the temperature of the water rises in the spring and summer and nutrient concentration is optimal, *P. globosa* forms a large biomass. *P.globosa* was identified as a potentially harmful species for several reasons. First, it releases dimethyl sulfide gas (DMS), which can irritate people's eyes, skin, and

60 respiratory system (Riegman and Van Boekel, 1996). Second, mucopolysaccharides are abundant in its colonies (Zhu et al., 2021). These polysaccharides are broken up by external factors like turbulence as well as internal factors like lysis and aging, which cause the accumulation of a thick, odorous foam on the coast. Besides*,* needle-shaped *Pseudo-nitzschia* can stick into *P. globosa* colonies and form structures that irritate filter feeders during *P. globosa* blooms (Sazhin et al., 2007). These structures can also injure fish, making them more susceptible to bacterial and viral infections (Lefebvre and Devreker, 2023).

65 Moreover, the neurotoxin domoic acid (DA) produced by *Pseudo-nitzschia* is responsible for the neurological disorder known as amnesic shellfish poisoning (ASP) in humans (Bates et al., 2018; Petroff et al., 2021). Additionally, marine mammals and

seabirds may get poisoned if they consume DA-contaminated planktivorous prey (Delegrange et al., 2018).

The French monitoring of phytoplankton population and associated environmental factors in the Eastern English Channel (ECC) started in 1979 with RNO (Réseau National d'Observation) or RNC (Réseau Nationale de Contrôle). Then, in 1984, a national network called REPHY (le REseau de surveillance du PHYtoplankton et des phycotoxines) was established by Ifremer to estimate the abundance and taxonomic composition of phytoplankton, describe their spatio-temporal dynamics, detect toxin-producing species, monitor, and alert for harmful blooms (https://doi.org/10.17882/47248). After that, in 1992, the Artois-Picardy Water Agency and Ifremer decided to establish SRN (Suivi Régional des Nutriments) to accurately monitor nutrient concentration (Lefebvre and Devreker, 2023). Although these monitoring networks enhanced our knowledge of phytoplankton dynamics, they remain inadequate to thoroughly understand recurrent, rare and extreme events occurring in the marine environment.

In 2004, the MAREL (Mesures Automatisées en Réseau pour l'Environnement Littoral) Carnot monitoring station was installed in the French part of the ECC. The MAREL Carnot station, developed and implemented by Ifremer (French Research Institute for Sea Exploitation), is a moored buoy protected by a tube and equipped with physical, chemical, and biological measuring devices and sensors that operate continuously and autonomously. This multi-sensor station is located in the Boulogne-sur-Mer harbor (Eastern English Channel), which is influenced by both marine and fresh water. It is equipped with high-performance systems for seawater analysis and data transmission in near real time. It measures the following parameters with high frequency resolution (20 minutes): estimated sea level, wind direction relative to true north, horizontal wind speed, photosynthetic active radiation PAR, sea water temperature, practical salinity, pH, dissolved oxygen, oxygen saturation, fluorescence, and turbidity. For nutrients, including nitrate, phosphate, and silicate, the sampling frequency is set to 12 hours.

2. Objectives

The purpose of this article is to describe the MAREL Carnot dataset and provide an overview of the variability of its physical, chemical, and biological parameters. For future users of the related dataset, we will offer a thorough description of the MAREL Carnot station, including its deployment and measurements. Based on previous research papers, we aim to demonstrate that the MAREL Carnot dataset can be used to evaluate the environmental or ecological status and conduct research in marine phytoplankton ecology and oceanography.

3. Materials and Methods

3.1 Location and Study Area

The MAREL station was installed on the Carnot sea wall in 2004, hence the name MAREL Carnot. It is located at 50.7405° N and 1.5677° E on the French side of the Eastern English Channel, near the exit of the port of Boulogne-sur-Mer, which is France's greatest fishing port in terms of annual tonnage. **Figure 1** below depicts the location of MAREL Carnot station on

the map.

There is no seasonal pycnocline in the Eastern English Channel (ECC), and stratification is limited and sporadic depending on freshwater discharge levels. Water can be extremely turbid due to the continental shelf nature of its seabed, which can reach a maximum depth of 180 m depending on tidal regimes. The ECC has a macro-tidal regime in the Dover Strait that varies from 3 m to 9 m during neap and spring tides, respectively (Jouanneau et al., 2013). This regime produces significant residual tidal currents from the English Channel to the North Sea, as well as high tidal currents that are nearly parallel to the shore. Fluvial supplies distributed throughout the French coast from the Bay of Seine to Cape Gris-Nez form a nearshore coastal water mass that is protected from the open ocean by a frontal area (Brylinski et al., 1996). This coastal water mass is tide-dependent and can extend from 3 to 5 miles offshore (Brylinski et al., 1991). The frontal area plays a significant role in structuring biological and non-biological exchange between coastal and offshore water masses. It is more sloped from the vertical during neap tides, resulting in a greater surface of exchange between the two water masses (Brylinski et al., 1991). Thus, particle and nutrient movement between inshore and offshore water masses is greater during neap tides than during spring tides (Lefebvre and Devreker, 2023).

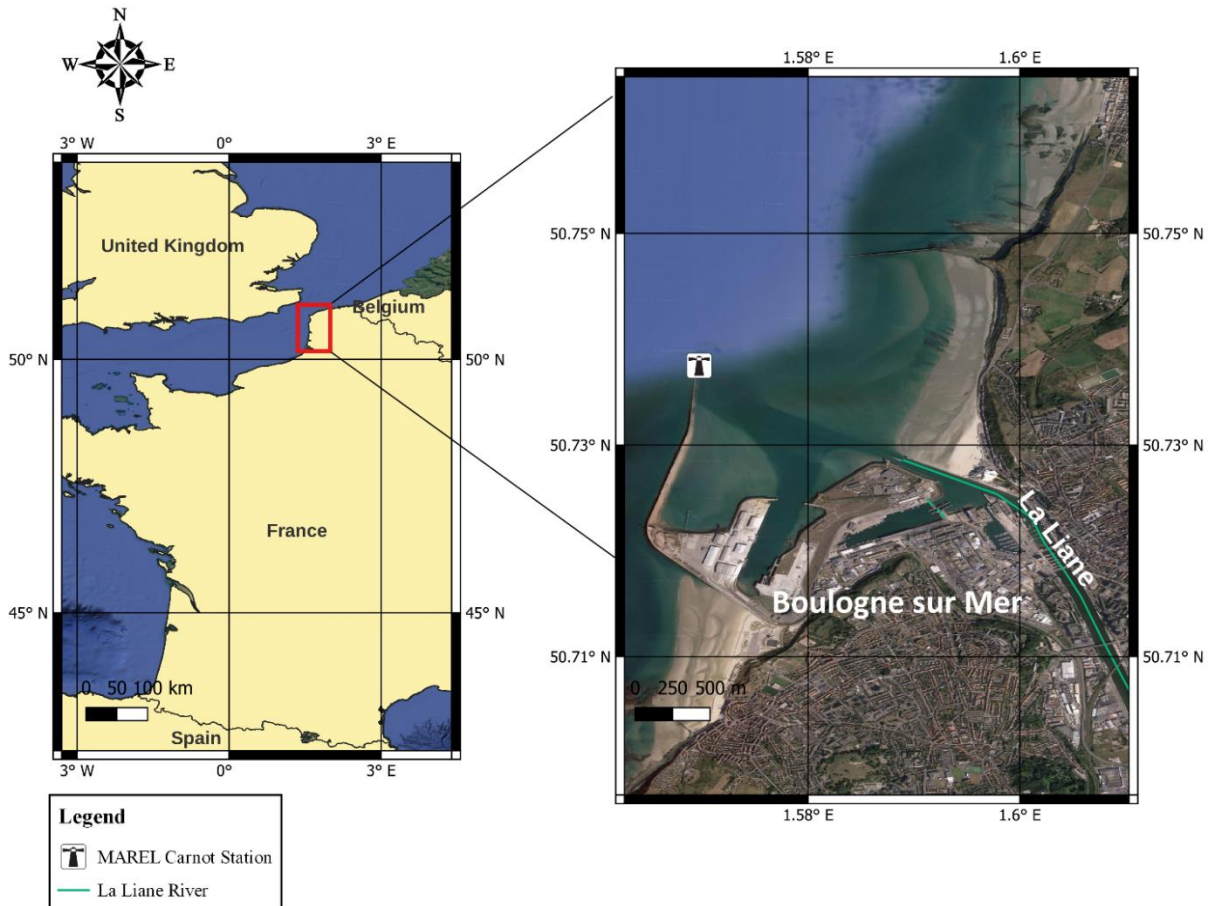



Figure 1 Location of MAREL Carnot station in the Eastern English Channel (EEC) (Map data © 2022 Google).

3.2 Description of the MAREL Carnot Station

MAREL is a French acronym for Mesures Automatisées en Réseau pour l'Environnement Littoral (automated sampling network for coastal waters). It belongs to a network of fixed platforms extending across the entire French coast called COAST-HF (https://coast-hf.fr), which is a component of the ILICO research infrastructure at the French national level (https://www.ir-ilico.fr/). MAREL Carnot station consists of a tube weighing 12 tons and measuring 15 meters in length. Because MAREL Carnot is located in a macrotidal zone, it is encased in a tube to be protected from strong currents, frequent storms, and boat collisions near the port. Indeed, buoys are not designed to withstand such challenging environments, so an infrastructure to maintain the buoy in a specific location and provide necessary protection was required. However, such an infrastructure would be huge and expensive, so the tube was the best solution. **Figure 2** shows the MAREL Carnot station, consisting of the MAREL tube and the lighthouse platform which is used for meterological sensors.

Its sensors are placed on a float inside the tube in order to follow tidal movements. A pulley system is placed in a chamber inside the harbor structure to manage the cables during high and low tides and to easily lift the station for maintenance when needed. Until 2014, it was made up of a measurement cell containing several sensors. The seawater was pumped upward to be analyzed. During periods when there were no measurement cycles, the system was chlorinated via electrolysis to prevent biofouling. Water was extracted from the subsurface at an approximate depth of 1.5 meters and then sent to a measurement chamber to be redistributed to different sensors.

The first version of the measuring system was constructed using electronic, computer, and mechanical equipment that date back to the 1990s. Some of these elements deteriorated over time, particularly those submerged in seawater, and had to be replaced with new equipment. In 2014, the prior measuring equipment was replaced with a new automated measuring probe. The objective was to conduct direct in-situ measurements using an in-situ multi-parameter probe. Thus, water circulation in the chamber was no longer performed to avoid air intake which would compromise measurements and data quality. The replacement of the old measuring system with a new one consumed time due to financial and technological challenges, and hence most of the data for 2014 is missing. **Table 1** shows the characteristics of the sensors installed on MAREL Carnot from 2004 to 2022. Sensor calibration was performed on a regular basis, usually every three months.

Table 1 The characteristics of the senors installed on MAREL Carnot station from 2004 to 2022

Parameter	Level of measurement	Sensor	Accuracy	Duration
Sea Water Temperature	1.5 m below water (Level 1)	Pt100	± 0.1°C	2004–2014
		NKE MP6	± 0.05°C	2014–2022
Practical Salinity	1.5 m below water (Level 1)	NKE MP6	± 0.1 PSU	2014–2022[a]
Electrical Conductivity	1.5 m below water (Level 1)	InduMax H CLS 52	± 0.3mS/cm [b]	2004–2014
		NKE MP6	± 0.05 mS/cm	2014–2022
Turbidity	1.5 m below water (Level 1)	TurbiMax W CUS 31	± 10%	2004–2014
		NKE MP6	± 5%	2014–2022
Dissolved Oxygen	1.5 m below water	OxyMax W COS 31	± 0.2 mg/L	2004–2014
		NKE MP6	± 5%	2014–2022
Fluorescence	1.5 m below water (Level 1)	SeaPoint Chlorophyll Fluorometer	± 10%	2004–2014
		NKE MP6	± 5%	2014–2022
PAR	28 m above water (Level -1)	LI-COR Sensor	± 5%	2004–2010
		Seabird PAR Satlantic	± 5%	2010–2022
pH	1.5 m below water (Level 1)	Orbisint CPS11	± 0.2	2004–2014
		NKE MP6	_[c]	2014–2022
Nutrients (Nitrate + Nitrite, Phosphate, Silicate)	1.5 m below water (Level 1)	SYSTEA NPA: Nutrient Probe Analyzer	± 5%	2004–2010
Wind Speed	28 m above water (Level -1)	ROWIND CV3F wind vane anemometer	± 15% RMS for Wind Speed <3.6 m/s ±6 % RMS for Wind Speed >3.6 m/s	2004–2015
		AirMAR 200WX	±5%	2021–2022
Wind Direction	28 m above water (Level -1)	ROWIND CV3F wind vane anemometer	± 2°	2004–2015
		AirMAR 200WX	±3°	2021–2022
Air Temperature	28 m above water (Level -1)	ROWIND CV3F wind vane anemometer	±1.5°C	2004–2015
		AirMAR 200WX	±5%	2021–2022
Estimated Sea Level	Sea surface (Level 0)	Hydro Ranger PLUS Siemens	-	2005–2014

[a]Salinity was derived from Conductivity before 2014

140 [b]The conductivity data before 2014 were deleted by Coriolis

[c] pH sensor failure after 2015

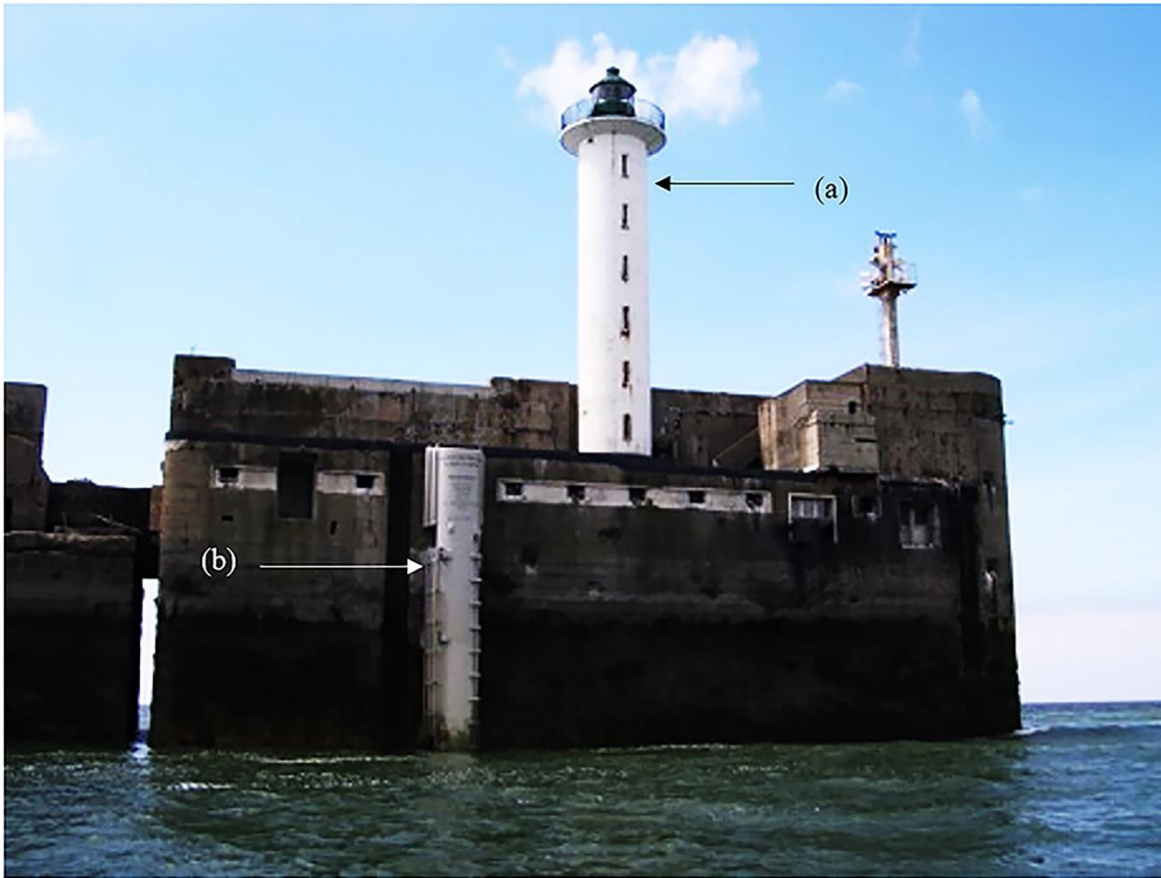



Figure 2 MAREL Carnot station consisting of the lighthouse (a) and the MAREL Carnot tube (b) (photo © Ifremer).

3.3 Measured and Calculated Parameters

145   The MAREL Carnot multi-sensor station measures physical, chemical and biological parameters in a continuous and autonomous mode. With a sampling frequency of 20 minutes, it is capable of providing high resolution data for conductivity (Siemens per meter), water and air temperature (degree Celsius), pH, fluorescence (Fluoresceine Fluorescence Unit), turbidity (Nephelometric Turbidity Unit), dissolved oxygen concentration (milligram per liter), **P**hotosynthetically **A**ctive **R**adiation or P.A.R (micromoles per square meter per second, or microEinsteins per square meters per second), wind direction (degree),

150   gust wind direction (degree), wind speed (meter per second) and gust wind speed (meter per second), relative humidity (percentage), atmospheric pressure (hectoPascal) as well as sea level (meter). On the other hand, nutrient concentration like nitrate, phosphate, and silicate were only measured once every 12 hours in order to limit the amount of chemical reagents required for the in situ analysis. Apart from salinity, which was calculated from conductivity prior to the installation of the NKE MP6 sensor in 2014, the only estimated parameter is sea level. **Table 1** shows the different parameters measured by

155   MAREL Carnot station.

3.4 Pre-processing of MAREL Carnot dataset

Data acquired by MAREL Carnot station are transmitted in near real-time to the Coriolis data center. Coastal CORIOLIS, or simply CORIOLIS, is a data portal for all in situ data platforms in Coastal French waters, including MAREL Carnot (https://data.coriolis-cotier.org). After downloading the dataset, the variables represented in **Table 1** are selected and several pre-processing steps were performed including offset correction and NA transformation, quality code (QC) extraction and correction, sensor and expert range correction, and time alignment (**Figure 3**). The subsections below provide details for each step.

Raw Data

Data Pre-processing Steps

1- Offset Correction & NA Transformation

2- QC Extraction & Correction

3- Sensor & Expert Range Correction

4- Time Alignment

Data Visualisation

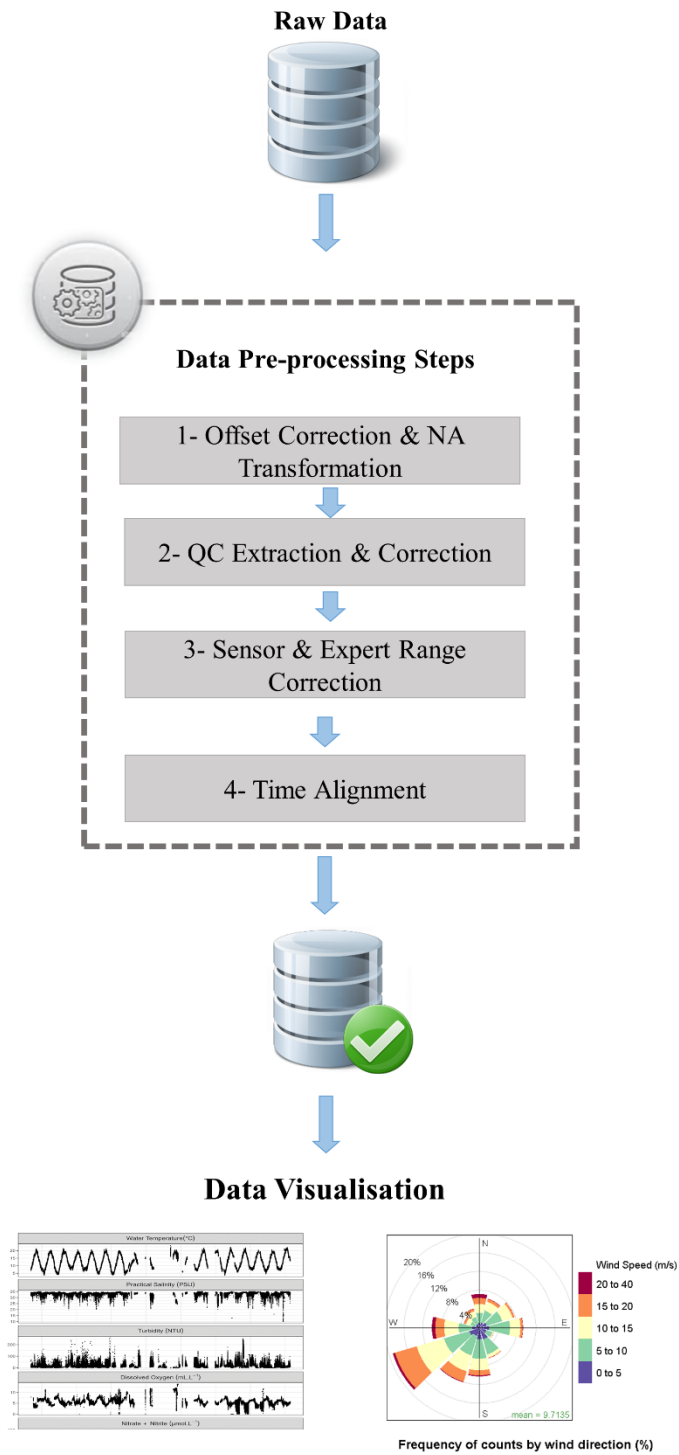



Figure 3 A simplified overview of the pre-processing steps and data visualization

3.4.1 Offset Correction and NA Transformation

We corrected the offset present in the photosynthetically active Radiation (PAR) and salinity variables. Then, we noticed that some nutrient values were present on Level 2. Since no measurements are carried out at Level 2 in MAREL Carnot, these measurements were deleted.

In addition, missing values in datasets are typically represented as NA, which stands for *Not Available*. However, in some cases, NA values are replaced with other numbers such as 77.77, 7777, 999, 999.999, 9999.99. A dataset may also include values like Inf and Nan, which stands for infinity and Not A Number, respectively. Because these types of observations can affect or even obstruct further processing steps, we convert them into something feasible, which is NA.

3.4.2 Quality Code Extraction and Correction

CORIOLIS quality control procedures provide the users with the quality of each measurement as a Quality Code (QC) (**Table 2**). Quality codes are assigned according to the Argo Quality Control flag scale (Wong et al., 2022), and are part of the CORIOLIS harmonized procedure applied to all its in situ data platforms.

In the raw dataset, the quality codes are present in one single column and requires deserialization. To extract the quality code of each observation, we deserialized the QC data and returned it into a matrix. According to Argo quality control manual, measurements given a QC 4 are not to be used. A flag '4' is assigned when a relevant real-time QC test has failed, or for bad measurements that are known to be not adjustable, e.g. due to sensor failure (Wong et al., 2022). Thus, all data with QC =4 (Bad data) were deleted, and replaced with *NA* values.

At the end of this step, we converted the dissolved oxygen measurements from milliliter per liter into milligram per liter according to Aminot & Kérouel, (2004) using Eq. (1)

$$DO\ (mg\ L^{-1}) = 1.429\ \times DO\ (mL\ L^{-1})$$

(**1**)

Even after QC correction, the data may still contain errors. For instance, a pH measurement of 1 might not have a quality code of 4, and will therefore appear correct despite being false. For this reason, we performed sensor and expert range correction to remove values that are unusual in marine coastal waters.

Table 2 Significance of the quality code (QC)

Quality Code	Significance
0	No Quality Code was performed
1	Good data
2	Probably Good data
3	Probably bad data that are potentially correctable
4	Bad data
5	Value Changed
6	Not Used

7	Not Used
8	Interpolated Value
9	Missing Value

3.4.3 Sensor and Expert Range Correction

The sensor range is a range of correct values from the highest possible measurement to the lowest possible measurement set
by the manufacturer. The expert range is a range of correct values set by a field expert. The sensor range was obtained from
the information provided by the sensor suppliers and MAREL (Ifremer), whereas the expert range was derived from expert
knowledge acquired in the studied area through previous research activities. For all parameters, only the values that fall within
the sensor and expert ranges are kept. Values that fall outside of the ranges are replaced with NA (*Not Available*).

The expert range and the sensor range are represented in **Table 3**. Indeed, the expert range is more precise than the sensor
range. For instance, the sensor may give us a salinity value of 38, but our specialists know that salinity can only reach 35 in
the Boulogne sur mer, so the sensor's result is qualified as false and must be removed.

Table 3 Sensor and expert ranges of parameters measured by MAREL Carnot

Parameter	Given Name	Unit	Sensor Range		Expert Range
			Old	New	
Fluorescence	Fluorescence_FFU	FFU	–	–	0–120
pH	pH	-	0.001–14	0–14	6.5–9.5
Practical Salinity	Salinity_PSU	PSU	–	2–42	5–35
Electrical Conductivity	Conductivity_S_m	S m^{-1}	–	0–7	3–6
Sea Water Temperature	Water_Temp_degreeC	°C	-5–30	-5–35	0–30
Air Temperature	TempAir_degreeC	°C	-10–50	-40–80	-10–45
P.A.R (Photosynthetic Active Radiation)	PAR_micoE_m2_s1	µmol m^{-2} s^{-1}	–	–	0–2500
Turbidity	Turbidity_NTU	NTU	0–4000	0–2000	0–270
Nitrate + Nitrite Concentration	Nitrate_Nitrite_micromol_l	µmol L^{-1}	0–100	-	0–100
Phosphate Concentration	Phosphate_micromol_l	µmol L^{-1}	0–100	-	0–10
Silicate Concentration	Silicates_micromol_l	µmol L^{-1}	0–100	-	0–50
Dissolved Oxygen	OxyDissolved_mg_l	mg L^{-1}	0–20	0–16	0–20*
Oxygen Saturation	OxygenSaturation_percent	%	-	0–120	0–120

Horizontal Wind Speed	WindSPD_m_s	m s^{-1}	0–50.93	0–40	–
Wind Direction Relative True North	WindDIR_degree	degree	0-359.9	0–359.9	0–359.9
Gust Wind Speed	Gust_WindSPD_m_s	m s^{-1}	0 – 50.93	0–40	–
Gust Wind Direction	Gust_WindDIR_degree	degree	–	0–359.9	–
Relative Humidity	RelativeHumidity_Percent	%	0–100	0–100	–
Atmospheric Pressure	Atmospheric_Pressure_hPa	hPa	–	300–1100	–
Estimated Sea Level	SeaLevel_m	m	–	–	0–20

* Value determined for the entire period from 2004 to 2022

3.4.4 Time Alignment

205 The measurements of the various sensors are not taken at the same time, resulting in a time lag that can range from few seconds to several minutes. In addition, the series may contain duplicates in some cases. Before statistical methods can be applied to the dataset, it must have an identical time interval between each measurement.

In order to synchronize the dataset and eliminate potential replicates, we performed a time alignment step. After extracting the day, month, years and hours initially present in the raw dataset, we extracted the minute's column and set minutes 0 through
210 19 to 10, 20 through 39 to 30, and 40 through 59 to 50. From this, we generated a time sequence of 20 minutes interval and merged it with the original data. After that, we aggregated the data at the obtained regular time step (20 minutes). If multiple measurements of the same variable exist within the same time step, the maximum, minimum, or average can be returned. In order to focus on the most critical environmental conditions posing risk of eutrophication, the maximum value was chosen for all parameters except oxygen where the minimum value was chosen. The QC value of each observation was then retained, and
215 a quality code of 9 was assigned to all NA values, including those removed by previously mentioned pre-processing steps.

4 Results and Discussion

Table 4 represents the descriptive statistics for the main parameters measured by MAREL Carnot from 2004 until 2022. The results show a high percentage of missing data, denoted as NA, or *Not Available*. Missing data is a major problem in time series. It is primarily due to sensor failure, communication problems, or sensor maintenance disability.

220

Table 4 Statistical summary (minimum, first quartile, median, mean, third quartile, maximum, and percentage of NA) of the parameters measured by MAREL Carnot station

Parameters (Units)	Min	Q1	Median	Mean	Q3	Max	percentage of NA
Air Temperature (°C)	-6.18	7.82	11.9	11.710	16.11	35	56.873
Gust Wind Direction (°)	7.8	124.55	226.3	205.176	271.5	359.9	94.622
Gust Wind Speed (m s^{-1})	0	7.27	11.24	12.282	16.24	50.9	61.532

Photosynthetic Active Radiation (μmol m^{-2} s^{-1})	0	0	34.7	280.850	361.8	2497.34	60.110
Relative Humidity (%)	25.21	74.07	82.05	81.039	88.99	100	63.447
Wind Direction (°)	0	92	198	177.989	246	359.9	61.414
Horizontal Wind Speed (m s^{-1})	0	5.78	9.08	9.737	13.14	50.82	61.511
Estimated Sea Level (m)	5.43	8.08	10.2	10.280	12.32	15.84	73.091
Water Temperature (°C)	3.6	8.73	12.8	12.935	17.3	23.5	30.276
Electrical Conductivity (S m^{-1})	3	3.601	3.944	3.991	4.411	4.959	69.017
Dissolved Oxygen (mg L^{-1})	0	6.844	7.990	8.051	9.210	17.01[*]	37.049
Fluorescence (FFU)	0	0.51	1.07	3.004	2.46	116.59	25.933
Nitrate + Nitrite (μmol L^{-1})	0.02	5.23	10.905	15.213	21.947	98.89	99.366
Oxygen Saturation (%)	0	83.69	91.573	88.582	97.11	120	70.150
Phosphate (μmol L^{-1})	0	0.44	0.65	0.719	0.86	10	99.426
pH	6.5	7.92	8.1	8.137	8.38	9.33	67.186
Practical Salinity (PSU)	8.7748	32.98	33.56	33.225	34.01	35	31.525
Silicate (μmol L^{-1})	0	1.9625	4.135	5.145	7.3175	39.25	99.326
Turbidity (NTU)	0	4.634	8.9105	14.624	17.3	259.7	32.212
Atmospheric Pressure (hPa)	980	1011	1018	1016.964	1024	1044	94.622

[*]Value obtained before 2014

Figure 4 and **Figure 5** show the time series of parameters collected from MAREL Carnot station from 2004 until 2022. We noticed that some signals have seasonal cycles, such as water and air temperature as well as photosynthetic active radiation (PAR). In addition, the signals contain episodic or continuous missing values over several time periods. For instance, a large number of missing values can be found around the year 2014 in most time series. This is due to station and sensor alterations that occurred during that time, particularly, the replacement of several sensors with a multi-parameter probe (Lefebvre and Schmitt, 2016). Likewise, the signals of air temperature, PAR, wind speed as well as sea level have been lost for several years while waiting for new funding resources to ensure the renewal of sensors and associated electronic systems. Conductivity data prior to 2015 were deleted by Coriolis data center, probably under the presumption that salinity is more relevant to the scientific community. This highlights the added value of our research, which is to ensure that all observations collected by MAREL Carnot remain permanently available and accessible to everyone.

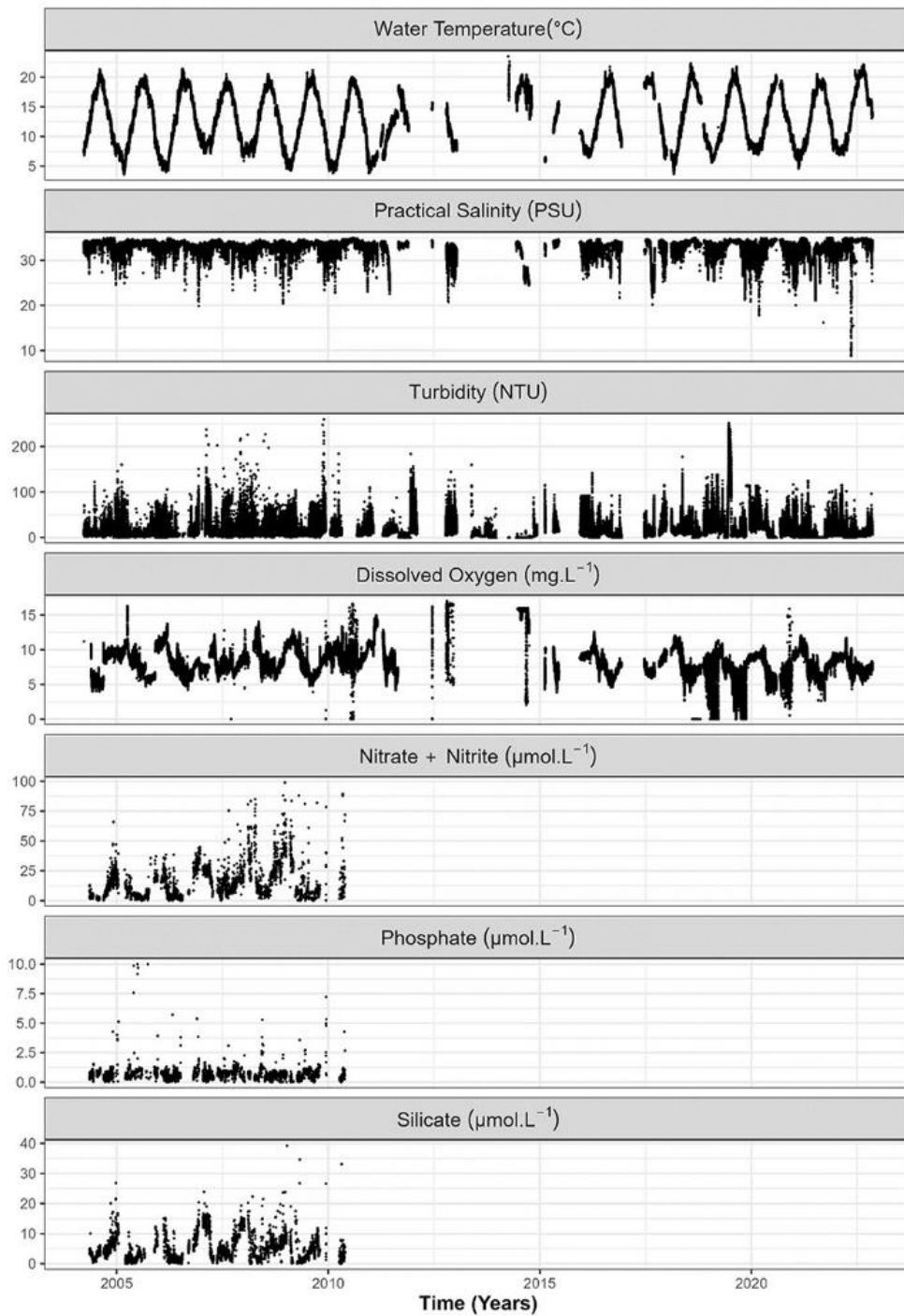



Figure 4 Time series of parameters collected from MAREL Carnot station during the period 2004-2022

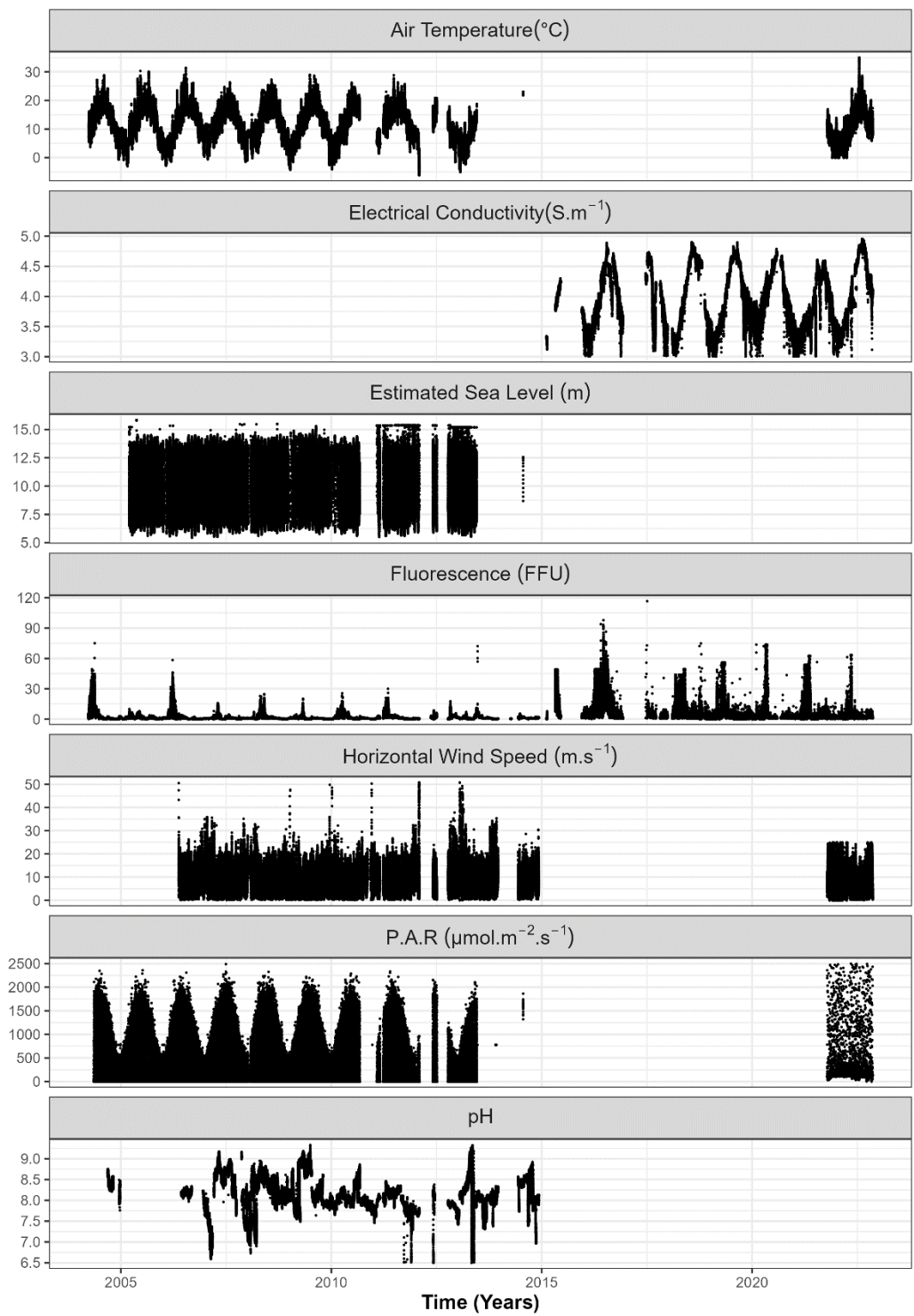
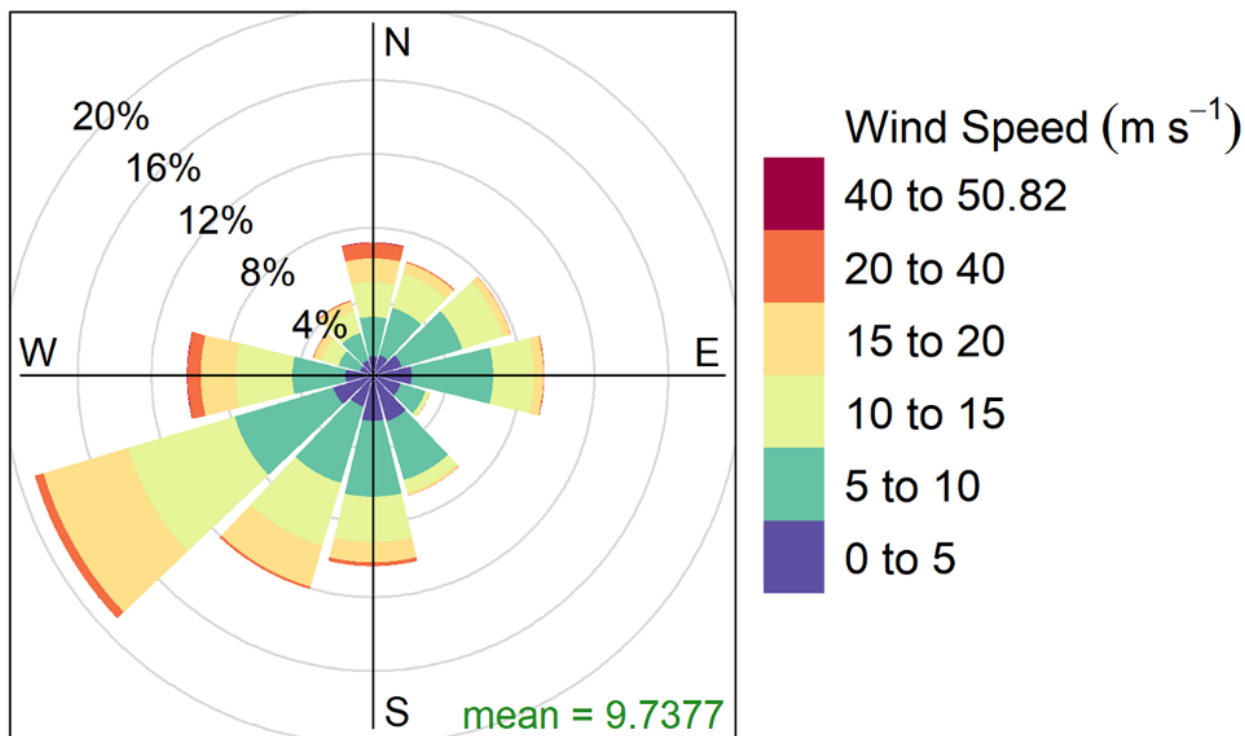



Figure 5 Time series of parameters collected from MAREL Carnot station during the period 2004-2022

245 Nutrient signals such as phosphate, nitrate, and silicate are only available until 2010. This is caused by a previous sensor failure and the inability to replace it.

Figure 6 shows a wind rose showing the frequency (%) and wind speed (m s⁻¹) for different wind directions measured by MAREL Carnot from 2004 until 2022.

250 **Figure 6 wind rose showing the frequency (%) and wind speed (m s⁻¹) for different wind directions measured by MAREL Carnot station from 2004 until 2022**

Scientists from several disciplinary backgrounds have utilized MAREL Carnot data to accomplish a wide range of research objectives. In the following paragraphs, we will go over some of the most significant findings from several research efforts. The scientific community that is interested in the MAREL Carnot dataset may find this evaluation useful in determining which
255 topics may or may not require further study based on the results of this evaluation. This dataset allows researchers to investigate the dynamics of phytoplankton as well as detect blooms caused by human activities and/or climate change.

For instance, Rousseeuw et al., (2015) developed an unsupervised Hidden Markov Model (uHMM) for monitoring the marine environment, specifically for detecting algal blooms and understanding phytoplankton dynamics. In their unsupervised Hidden Markov Model, uHMM parameters were estimated using spectral clustering rather than the commonly used iterative

260   Expectation Maximization. The results obtained using MAREL Carnot dataset showed that the proposed system is efficient to detect the main productive and non-productive periods, as used for the purposes of the EU Water Framework Directive to assess good environmental status, and refine knowledge about phytoplankton bloom dynamics in a temperate ecosystem, temporarily dominated by a harmful algae, *Phaeocystis globosa*. Thus, the suggested uHMM system successfully characterizes phytoplankton dynamics from new incoming data (in near real-time), and will enable researchers to gain a better understanding

265   of the main controlling or forcing parameters (e.g., nutrient pressure, light availability, turbidity), the environmental status (e.g., phytoplankton biomass), and the direct and/or indirect effects of algal blooms (e.g., oxygen concentration) (Rousseeuw et al., 2015).

     Following Rousseeuw et al., (2015) unsupervised approach, Grassi et al., (2019) suggested a Multilevel Spectral Clustering (M-SC) to split multivariate time series from general patterns to extreme events without *a priori* knowledge. The results

270   obtained from MAREL Carnot dataset have shown that we can extract knowledge on dynamics of events or environmental states. In addition, it was shown that M-SC allows unsupervised labelling of time series, which is a basic part of machine learning needed to build an event prediction system and improve sampling strategies to become in near real time (Grassi et al., 2019). As a result, scientists should be able to create a HAB early warning expert system to warn shellfish farmers, and prevent both public health risks and commercial losses in the shellfish farming business.

275   The application of M-SC and uHMM on MAREL Carnot dataset can reveal rare, recurrent and extreme events, which may aid in improving coastal assessment and defining what constitutes a desirable environmental state. This can indirectly help improve management strategies established by the Water Framework Directive (WFD), Marine Strategy Framework Directive (MSFD) and Oslo and Paris Convention (OSPAR).

     MAREL Carnot dataset can be also be beneficial to data scientists and machine learning specialists. This dataset contains some

280   missing data due to sensor failure, and harsh weather conditions that prevent immediate sensor maintenance. It was used to evaluate the performance of a proposed Dynamic Time Warping method to fill in successive missing values of univariate time series (Phan et al., 2017b), and low uncorrelated multivariate time series (Phan et al., 2017a). It was also utilized in the application of a fuzzy logic-based similarity measure to impute large gaps of uncorrelated multivariate time series (Phan et al., 2018). These data imputation approaches are published on the Comprehensive R Archive Network (CRAN) and accessible

285   through DTWBI and DTWUMI packages, respectively.

     This dataset can also be utilized to assess the performance of time series analysis methods on marine datasets. For instance, Kbaier Ben Ismail et al., (2016) used four parameters measured by MAREL Carnot to compare the classical techniques of time series analysis to recent ones. Also, Huang and Schmitt, (2014) performed empirical mode decomposition (EMD) to study time dependent intrinsic correlation of temperature and dissolved oxygen time series measured by MAREL Carnot.

290   Derot et al., (2020) investigated the impact of different sampling frequency on forecasting harmful algal blooms. They applied Random Forest (RF) and sliding window strategy on 12 parameters derived from MAREL Carnot dataset. This research demonstrated that the sampling frequency has a direct impact on the forecast performance of a Random Forest (RF) model as high-frequency datasets might provide useful information to the RF. This type of model sets the groundwork for the creation

of a numerical decision-making tool that could help mitigate the impact of algal blooms, and can recreate interactions that

295   closely resemble the real biological processes (Derot et al., 2020).

Moreover, MAREL Carnot dataset might be useful for studying turbulence. Derot et al., (2015) studied the phytoplankton biomass during bloom events by applying Empirical mode decomposition (EMD) on fluorescence dataset from MAREL CARNOT. Results revealed that bloom events include considerable internal variations. Blooms are not smooth and "mountain-like", but exhibit high frequency oscillations due possibly to turbulent advection and complex population dynamics (Derot et

300   al., 2015). Besides, Zongo & Schmitt, (2011) demonstrated that pH fluctuations in marine waters are strongly influenced by turbulent hydrodynamical transport, and may be considered as a turbulent active scalar.

Moreover, the sensors placed on the lighthouse provide valuable data for meteorological research and may improve local weather forecasts by measuring variables including wind speed, wind direction and air temperature. Also, the MAREL Carnot high frequency dataset can be used to validate satellite-derived products such as fluorescence. It also provides measurements

305   for parameters that cannot be measured from space such as nutrient concentration (Lefebvre and Schmitt, 2016). Our dataset may assist fisheries research. For instance, Toomey et al., (2023) incorporated MAREL Carnot water temperature time series in the supplementary material of her study on the impact of temperature on Downs herring.

Overall, the MAREL Carnot station provides automatic, continuous, and long-term observation of various physical, chemical and biological parameters that enhance our knowledge about the environmental state of the coastal environment and bloom

310   events. Hence, MAREL Carnot dataset aligns with objectives of SRN (Suivi Régional des Nutriments in French, Regional Nutrients Monitoring Program), especially by assessing the influence of continental inputs on the marine environment, and their implication on possible eutrophication which can assist in estimating the effectiveness of development and management policies in the marine coastal zone (Lefebvre and Devreker, 2023). To clarify, MAREL Carnot is the first coastal sampling station for the SRN transect. Thus, it assists in understanding phytoplankton dynamics by determining recurrent, extreme and

315   rare events in this highly impacted and vulnerable coastal area.

Furthermore, MAREL Carnot dataset can be complementary to both REPHY (Observation and Surveillance Network for Phytoplankton and Hydrology in coastal waters) (https://doi.org/10.17882/47248), and REPHYTOX (Monitoring Network for Phycotoxins in marine organisms) (https://doi.org/10.17882/47251). The goal of REPHY is to measure the biomass, abundance, and composition of marine phytoplankton as well as hydrological parameters in coastal and lagoon waters.

320   REPHYTOX is designed to find and track three types of toxins that can build up in bivalve mollusks and cause DSP (Diarrheic Shellfish Poisoning), PSP (Paralytic Shellfish Poisoning), and ASP (Amnesic Shellfish Poisoning) (Belin et al., 2021). Monitoring carried out by MAREL Carnot in parallel with REPHY and REPHYTOX permits continuous adaptation to the objectives, developing analysis strategies with extensive and complex data, thereby ensuring sustainability, which were challenges faced by REPHY and REPHYTOX before.

325   While MAREL Carnot has made substantial progress toward automating marine ecosystem monitoring, there are still some significant challenges to overcome. Indeed, it can be interrupted by rough sea conditions, such as strong tidal currents and storms. In addition, biofouling presents a major problem for sensors in the coastal environment, which explains why only a

few moored autonomous systems have been deployed in the coastal environment (Blain et al. 2004). Due to sensor failure, phosphate, nitrate, and silicate measurements are not available after 2010. To better explain the large data gap, we should
330 emphasize that we were in an interim phase, facing difficulties in maintaining a system developed and built in the early 2000s, with electronic parts that were no longer available and waiting for the improvement of the smart multisensor marine observation platform, COSTOF2, which was driving all of the sensors and dataflow.

As our knowledge and understanding of coastal ecosystems is growing with time, the EOV (Essential Ocean Variables) and EBV (Essential Biodiversity Variables) might be updated in the future. This may necessitate the installation of new sensors on
335 MAREL Carnot station to measure these new variables or parameters.

In future work, we plan to use a multi-scale, multi-source, multi-criteria, and multi-parameter approach to characterize and predict harmful algal blooms in the Eastern English Channel caused by *Phaeocystis globosa* and *Pseudo-nitzschia spp.*. We will do this by combining high frequency datasets from MAREL Carnot, satellite, and modeling data with low frequency datasets from other sources. This integrated observing system will be used to identify environmental states present in the
340 region, and develop an early warning system that can anticipate harmful algal blooms in particular, as well as changes in water quality and environmental state in general.

4.1 Data Availability

The raw data are present on the official Coriolis website. "These data were collected and made freely available by the Coriolis project and programmes that contribute to it *(*http://www.coriolis.eu.org)." The dataset after quality control procedures are
345 present on the SEANOE website (DOI: 10.17882/39754) (MAREL Carnot, 2023) in file "2004-2022 Coriolis processed data" . Our data are made available according to the FAIR approach (Findable, Accessible, Interoperable, Reusable).

5 Conclusion

In conclusion, high frequency data from MAREL Carnot instrumented station are useful in many scientific fields, such as phytoplankton ecology, data science, and oceanography. It can be used to describe the environmental state and forecast algal
350 blooms in the Eastern English Channel, which is important to warn shellfish farmers and prevent economic losses and health problems. It can also be used with satellite, modeling, and low-frequency in situ data to enhance our understanding of the marine ecosystem.

Competing Interests

The authors declare that they have no conflict of interest

355 **Author Contribution**

Raed Halawi Ghosn wrote the paper. Alain Lefebvre led the conceptualization, the writing of the paper and he also led the funding acquisition, the scientific coordination of MAREL Carnot related activities since 2002.We highly appreciate the effort of Émilie Poisson-Caillault, Guillaume Charria, Armel Bonnat, and Michel Repecaud for their contribution in data pre-processing. We would also like to sincerely thank Jean-Vallery FACQ, Loïc QUÉMÉNER, Vincent DUQUESNE, and Camille
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