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Implications of low temporal resolution of vessel tracking systems

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Abstract

Spatial and temporal fishing effort (FE) estimates are crucial for informing scientific-based decisions in fisheries management, spatial planning, and conservation. Lower temporal resolution (longer intervals between vessel position registrations) reduces FE accuracy, thus calling for a balance between precision and feasibility for large-scale mapping, such as in European waters. Effective marine management is critically dependent on this kind of accurate, comprehensive, and appropriate data. New EU legislation mandates tracking all fishing vessels, including small-scale fisheries (SSF) (LOA $\leq$ 12 m), implying a reassessment of optimal polling intervals. While experts recommend high-frequency polling (1 poll/30 s) for SSF, large-scale fisheries (LSF) have been mapped with up to 2-h polling intervals. Here, our study evaluates how polling frequency affects fishing activity characterization and FE estimation across fleets. We found that low temporal resolution critically affects (1) FE by underestimation, (2) misclassification of fishing behaviour, (3) compliance challenges, (4) marine spatial planning conflicts, (5) seafloor impact assessment (6) inaccurate bycatch risk analysis, (7) geographic projection biases, and (8) CPUE-based abundance indices, affecting stock and mortality estimates. These results highlight a central problem: low-resolution tracking compromises the scientific and management of outputs. The promise of high-resolution tracking to improve accuracy, is affected by the trade-offs between cost and data processing capacity, and the burden on vessel operators. Thus, SSF and passive gears should be tracked with at least a 30-s polling frequency as a conservative approach. For LSF using active gears, further work is required to determine the optimal ping frequency, but overall, it should be on the scale of a few minutes, depending on the gear used. To address this, our work clearly supports a recommendation for future regulations to define minimum acceptable polling intervals, tailored by fleet segment, and that support mechanisms be implemented to ease adoption. These regulatory aspects should contemplate a close collaboration with the fishing industry to ensure practicality, compliance, and long-term success. Thus, our findings highlight the costs of low-resolution tracking, providing critical insights for decision-makers shaping future vessel monitoring policies.

Keywords: fishing effort; vessel tracking systems; temporal resolution; ping rate; polling interval, spatial grid

Introduction

Sustainable development of human activities in marine environments is one of most ambitious and urgent challenges in modern societies (i.e. see the EU Blue Growth agenda). In this context, proper spatial planning and integration of sea uses, including fisheries, are essential and must be combined with the long-standing emergence of sustainable exploitation of marine biological resources. Science, management, and enforcement are considered the three pillars of fisheries sustainability (Welch et al. 2024). Effective area-based management to ensure long-term sustainability requires informed decision-making based on accurate, comprehensive, and appropriate

data. Decision makers are striving to meet national and regional targets such as, e.g. good environmental status (e.g. Marine Strategy Framework Directive), which requires the best scientific support, and the capacity to plan ahead for compromises with data acquisition costs. A fundamental element in many environmental and fisheries management targets is the quantification of fisheries pressures and impacts, and therefore the spatial footprint of fishing activities. Conversely, other spatial uses such as offshore wind farms or Marine Protected Areas (MPAs) that hinder fishing can only be adequately assessed on their impact in fishing if the Fishing Effort (FE) is available at the highest possible temporal resolution.

FE represents the aggregated amount of fishing activity occurring on fishing grounds over a designated period, commonly specified for different types of gear and fleet segments. It can be estimated using indirect methods based on questionnaires, which produce FE maps with less spatial detail (Léopold et al. 2014, Thiault et al. 2017, Grati et al. 2022). However, in many countries (e.g. EU and USA), FE reporting is based on fisheries logbook registrations and/or, in more detail, estimated using spatial trackers located on the fishing boats. These trackers provide the vessel's position at different time intervals (along with speed and bearing, or heading, or course of the fishing vessel), generally named ping rate, polling interval, or temporal resolution.

Currently, boats are tracked using Vessel Tracking systems mostly relying on Global Navigation Satellite Systems (GNSS) usually working as Vessel Monitoring Systems (VMS), Automatic Identification Systems (AIS), or Mobile Tracking Systems (MTS). Each of these has distinct features, costs, and advantages, as summarized in Quincoces (Quincoces 2021). VMS transmits vessel latitude–longitude location, speed, heading, and ID via satellite at regular intervals. It offers high data security, since it's not publicly accessible, and provides comprehensive coverage of fishing activity. AIS, initially developed for maritime safety under SOLAS (International Convention for the Safety of Life at Sea, IMO, 2002), is mandatory for merchant vessels over 300 GT and, since 2014, for EU fishing vessels longer than 15 meters. It uses radio signals with shore-based and satellite receivers, providing valuable data for traffic monitoring and safety, though coverage varies extensively. AIS can also be turned on and off by the boat operators. It is widely available to the public, thus, not being confidential. MTS, grouping tracking systems including mobile phones and low-cost tracking systems, generally offers the highest spatial and temporal resolution, are weather-resistant, affordable (<100€/device), and are widely accessible. However, these generally require onboard installation (except if it in a mobile phone app) and maintenance (or that an operator carries it), can suffer signal loss in remote or obstructed areas (including intentional interference), and unlike VMS or AIS, the data can be owned by the device's MTS owner.

The introduction of VMS as a surveillance and enforcement tool provided information on the locations of individual fishing vessels and the complete or almost complete coverage of many fleets (Amoroso et al. 2018). Besides estimating the FE or fishing pressure, this type of data has been used in a plethora of fields, namely in stock assessment (Bordalo-Machado 2006, Punzon et al. 2016), fishing behaviour and dynamics (Letschert et al. 2025, Vermard et al. 2010, Watson and Haynie 2016, Stelzenmüller et al. 2024), trawling impacts on

species, habitats (Lopez et al. 2020), and ecosystem processes at regional scales (Lambert et al. 2014, Pitcher et al. 2016, Eigaard et al. 2017), economic, social and socio-ecological system studies (Stelzenmüller et al. 2024), species distributions (Marshall et al. 2014), investigations about fishers strategies and behaviour (Russo et al. 2015), studies of the interaction between wild fauna and fishing vessels (Cianchetti-Benedetti et al. 2018), habitat mapping and modelling (Riley et al. 2024) and marine spatial planning (MSP; Fock 2008, Campbell et al. 2014, Bastardie et al. 2017, Stelzenmüller et al. 2022), including mapping fishing grounds (Jennings and Lee 2012, Wang et al. 2015, Maina et al. 2016), fisheries certification (Hiddink et al. 2023), advice on the location of protected areas (Fock 2008, Maina et al. 2016), and assessment of MPA effects (Dinmore et al. 2003, Murawski et al. 2005). In all these applications, it always emerges that the effects of spatial FE heavily depends on temporal resolution.

Shorter time intervals between tracking pings, i.e. higher temporal resolution, lead to more accurate characterizations of fishing activities and effort estimates. However, higher temporal frequency also increases the costs and data volume associated with tracking devices. Therefore, it is crucial to find a balance between accuracy and operational feasibility (including costs) to develop comparable FE maps over extensive areas such as European waters, encompassing all fleet segments.

Recent EU legislation (EU 2023/2842) mandates that all fishing boats in the EU, including small-scale fisheries (SSF $\leq$ 12 m), must be tracked, with the implementation being gradually phased until 2030. This highlights the need to reassess the optimal polling interval using robust quantitative methods. While high-frequency polling (1 poll/30 s) provides the most precise estimates and is advised for proper mapping of SSF, large-scale fisheries (LSF) have traditionally been mapped using polling frequencies up to 1–2 h. Interpolation is often employed to enhance temporal coverage (Hintzen et al. 2010, Russo et al. 2011a).

This current state of affairs calls for the need to provide advice on the best temporal resolution, both for SSF and LSF, usable at broad geographical scales and comparable among countries, as it is clear that the current 2-h frequency is not enough to respond to the increasingly frequent requests from advice data users (e.g. Natura 2000 areas, Offshore Wind Developments areas, and impacts on habitat types).

In the current work, a group of experts from 14 institutions across Europe aim at providing insights on how low temporal resolution in vessel tracking data can hinder effective decision-making in fisheries management by limiting the accuracy of FE assessments.

Current vessel position frequency (polling interval)

Each boat tracking position data is classified into fishing (e.g. hauling, deploying, and trawling) or non-fishing activities (e.g. steaming, traveling, and resting), either using a fixed speed threshold, statistical analysis or a machine-learning algorithm. This is necessary because the individual position data do not contain either information on whether the vessel is currently engaged in fishing activity, nor which specific fishing gear was used. The latter information must be taken from the relevant entry in the logbook of the respective fishing vessel, when it exists, or can eventually be inferred from the spatial behaviour

From geo-location to fishing effort

1. Geographic coordinates are recorded with a temporal interval, with a device in the vessel (e.g VMS, AIS, GPS)

2. Points are converted into fishing trips and classified (e.g. setting, trawling, no-fishing)

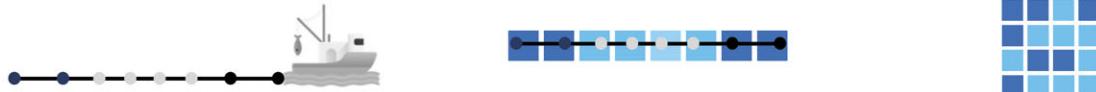**3. Fishing effort data is summarised in a spatial grid and mapped**

Figure 1. Summary of the main steps in producing FE indicators from tracking systems. VMS, AIS, or GNSS (e.g. GPS); geolocation consists of the recording of the time stamp and geographic position, namely, by tracking the vessels.

of the vessel (Russo et al. 2011b, Han et al. 2024). The fishing positions are then aggregated into a spatial grid (e.g. C-square) (Rees 2003) and a time interval (month or year) to produce maps of FE (Fig. 1).

The VMS has been mandatory since 2004 in the EU for all vessels larger than 18 m LOA, since 2005 for vessels larger than 15 m LOA and since 2012 for vessels larger than 12 m LOA (with the possibility of exceptions). According to the current EU Control Regulation Implementation Act (EU 404/2011, article 22), the vessel position shall be transmitted at least once every 2 h by VMS. This information is used by the scientific community, e.g. by employing the data that are requested annually by a VMS/Logbook data call issued by ICES (e.g. https://ices-library.figshare.com/articles/report/ICES_Data_call_2024_-Data_submission_of_VMS_Log_book_data/25846339), for mapping the fisheries activities at the finest possible scale (0.05 degrees c-squares, corresponding to around 15–20 km^2 depending on latitude). These data are processed and used for ICES advice to the European Commission, e.g. to estimate fishing pressure and impact on the seabed, and are available upon request for scientific works.

However, in some countries, AIS data at a higher resolution (generally 10-15 min) is freely provided by governments (e.g. Iceland, Norway, and Denmark) or can be requested by researchers (e.g. Germany and the Netherlands). Other countries have governmental or regional tracking devices installed on some fleet vessels, giving data with higher resolutions (e.g. 30 s) (e.g. Portugal, Spain, and Denmark), used for management, generally confidential. Global Fishing Watch has world estimations of FE based on AIS data, but its source is not available, and it is not made to be used for legal aspects. However, most AIS data do not include information from the logbooks as to which fishing gear was used. Although the need for higher resolution data has been recognised for a long time (Rijnsdorp et al. 1998, Nilsson and Ziegler 2006), obligations for such time intervals have probably been hampered by costs and technical capabilities. Innovative solutions incorporate electronic devices (such as logbooks) connected to MTS, providing information on catches and bycatch, gears, and fishing activities, which can be an alternative, although it does not exclude the need for higher temporal resolution (https://www.azti.es/wp-content/uploads/2025/02/Informe_final_Ebartesa_gestion_pesca_artesanal.pdf). Thus, if properly designed, an electronic logbook could be combined with relatively high-resolution data and, hence, limit the need for advanced classification methods. This approach, on the other hand, would heavily rely on fishers self reported data.

In terms of SSF, in many European countries, these fisheries are neither currently being tracked, nor do they have AIS equipment installed (or any other tracking device) (https://rpubs.com/MRufino/SSF_EU_Map). There are exceptions, such as certain case studies (ICES 2022, 2023 reports). In the new EU Control Regulation (EU 2023/2842) in addition to VMS, 'fishing vessels of less than 12 metres in length overall may carry on board a device, which does not have to be installed on board and which allows the vessel to be automatically located and identified while at sea through recording and transmitting the vessel position data at regular intervals through a satellite connection or any other network.' However, it is stated that Member States should be able to track all fishing vessels, including those that are <12 m in length overall, and should receive position data from them at 'regular and sufficiently short intervals.' Article 9 provides some further detail, but the position frequency is not specified, although the EU Commission is responsible for defining these details.

Consequences of low-resolution boats tracking data

The consequences of having lower-resolution data are summarized in Fig. 2, and explained in detail in the sections below.

FE indicators

Temporal resolution is crucial for accurately estimating FE both regionally (Rijnsdorp et al. 1998) and globally (Amoroso et al. 2018). The effect of temporal resolution on FE estimates varies depending on métiers and location. For example, while gadoid trawlers in the Barents Sea show a 30% underestimation in FE with a 2-h interval (Skaar et al. 2011), 53% underestimation was observed for Dutch beam trawlers in the North Sea (Hintzen et al. 2010), UK fishing vessels showed a 54% underestimation (Eastwood et al. 2007), and 60%–70% underestimation was found for Australian prawn fisheries (Deng et al. 2005). In the northwest US trawling fishery, a 19% improvement was noted when increasing polling frequency from 2 h to 1 h (Palmer and Demarest 2018). Katara and Silva (2017) found that in the Portuguese purse seine fishery, a 2-h interval missed 42% of fishing trips compared to a 10-m interval, skewing results towards longer trips. Overall, FE is often underestimated, likely with a spatial bias that varies across different regions.

However, few previous works have recommended an optimal ping rate for LSF, based on statistical analysis. Deng et al. (2005) simulated VMS data by subsampling GPS positioning
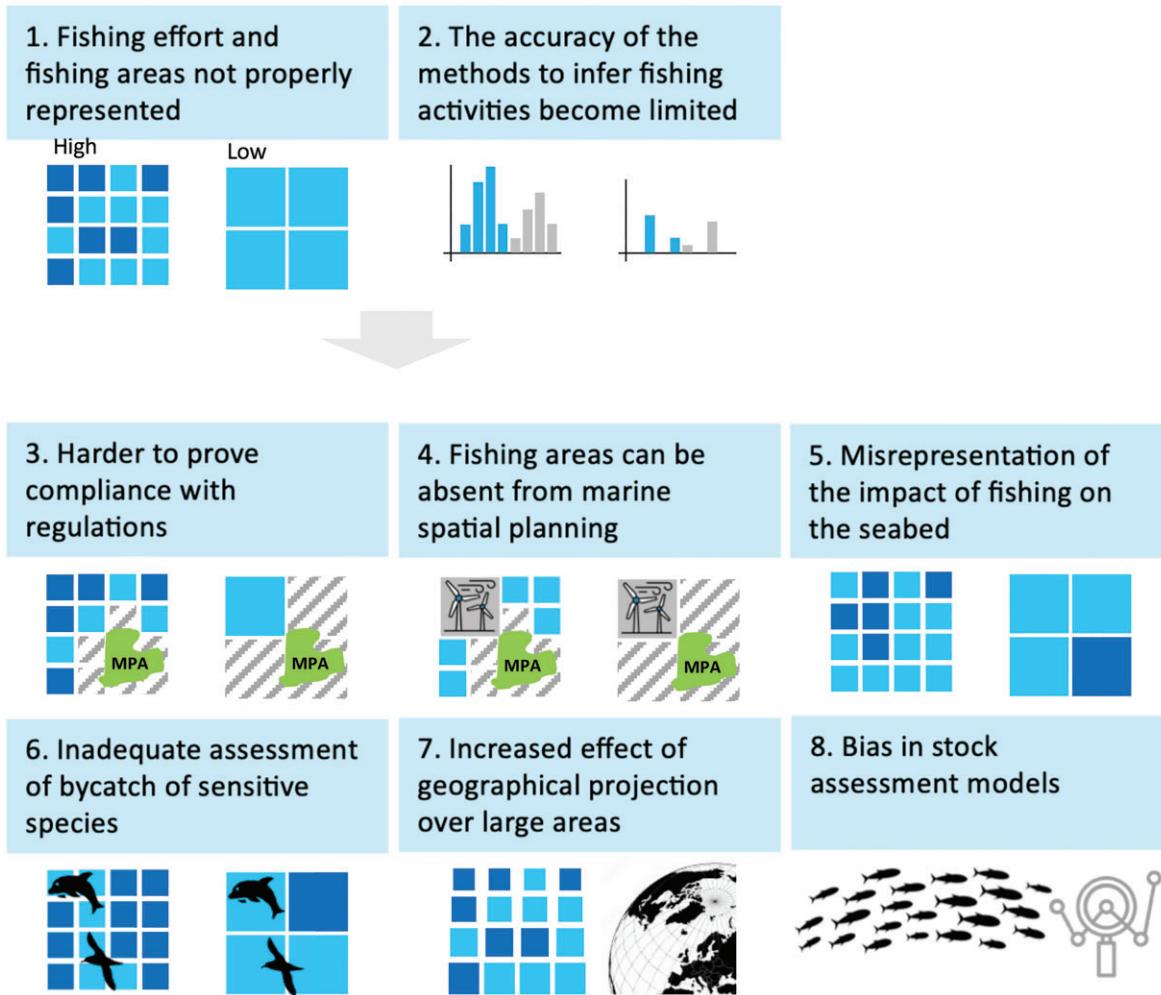
Figure 2. Summary of the main consequences or risks of inadequate temporal resolution of vessel tracking systems.

systems in a prawn fishery in Australia and concluded that polling intervals longer than 30 min could not accurately estimate trawl tracks. Palmer and Demarest (2018) considered that VMS polling intervals of 30 min along with linear interpolation between points, provided reasonable estimates of FE by management area, for trawlers in the northeast USA (15–120 min evaluated). Another illustrative example is provided by Scottish flyshooters, which typically take 20–30 min to shoot the entire gear. Each arm of the gear can extend from 1.5 to 3 km from each cod end, and the hauling speed is determined by the power of the winch, as the vessel remains in neutral. Hauling speeds vary significantly depending on current conditions and winch power, typically ranging from 2 to over 6 knots and the complete shooting and hauling process can take between 1.5 and over 2 h, depending on gear size and fishing depth. In such cases, a ping rate of 30 s is necessary to accurately map FE—lower-frequency pings may result in important information loss (Rui Catarino, pers. comm., unpublished information).

Additionally, other metrics of FE, that require distinguishing between setting and hauling for static gears, such as soak time (FE effort variables, EU Map 2021/1167), can also be affected by temporal resolution. Sans and Rodriguez (2023), using a gillnet fishery operating in the Bay of Biscay found that a resolution of 5 min was acceptable for identifying hauling events but not necessarily to identify the associated setting operations, for vessels >15 m LOA. In contrast, whereas for vessels <10 m, considering a time interval of 1 min, 99% of all fishing operations were retained, but increasing this period to 5 min, resulted in a loss of around 50% of setting operations and 10% of hauling operations.

However, aligning recommendations with realistic, incremental improvements to current data limitations is essential for effective implementation. For example, while the current VMS reporting interval for large-scale fleets (LSF) is typically 2 h, increasing resolution to 10-min intervals e.g., would provide a 12-fold improvement in spatio-temporal detail. This enhanced resolution would significantly refine the footprint of fishing operations, enabling more accurate delineation of specific activities such as gear setting and hauling, or even the positioning of individual gear components in passive fisheries (e.g. pots and hooks). Such detail may also complement or overlap with objectives of Remote Eletronic Monitoring (REM). Nevertheless, there are challenges when recommend-

ing a shift from 2-h intervals to near real-time or per-second resolution, which may be viewed as impractical by many management agencies, and risks being dismissed outright. Several factors contribute to this challenge, including (1) the increased costs associated with broadcasting high-frequency positional data via satellite-based VMS devices, (2) potential reluctance within the fishing industry to disclose fishing locations, and (3) the extended time at sea typical of LSF operations. Furthermore, in countries with large fleets or extensive fishing grounds, high-resolution tracking would generate vast quantities of data, including for non-fishing activities such as steaming, as current systems often lack the capacity to differentiate between fishing and non-fishing behaviour in real time. These considerations underscore the importance of proposing feasible, cost-effective steps that balance the need for improved data resolution with the practical constraints of implementation.

Despite advancements in tracking technologies, data storage and processing capabilities remain a limitation in several countries and should be considered a potential constraint, especially when scaling up temporal resolution. Fleet characteristics influence data volume, with LSF typically spending more time at sea and covering greater distances, whereas SSF undertake shorter trips with fewer days at sea. For example, the UK >12 m fleet recorded ∼2.5 million VMS messages in 2022. Increasing the resolution to 10-min intervals (a 12-fold increase) would result in roughly 30 million messages per year. Over 16 years (since 2009), this equates to ∼480 million records. File sizes would scale from ∼100 MB/year at 2-h resolution to ∼1.2 GB/year, totalling ∼20 GB over 16 years—a manageable size by current computing standards, though additional data from <10 m and inshore fleets would further increase storage demands. Cost is another important consideration. UK VMS devices, which operate via the Iridium SBD satellite network, incur transmission costs of €0.04–€0.16 per message or €15–30 per month. In 2022, transmitting 2.5 million messages cost an estimated €100 000; increasing resolution to 10-min intervals would raise this to ∼€1.2 million annually. While device acquisition and installation may be subsidized by government agencies, ongoing transmission and maintenance costs are typically borne by fishers. These costs, alongside concerns over disclosing precise fishing locations, could pose significant barriers to implementing higher-resolution tracking policies. This context should be carefully considered when formulating policy recommendations.

However, high-resolution positional data (e.g. at 5-, 10-, or 15-min intervals) do not necessarily require real-time transmission via satellite, which is costly. For example, as mentioned before, an effective alternative is delayed transmission via mobile networks at the end of a fishing trip, significantly reducing operational costs. This distinction underscores the different objectives for vessel tracking: real-time data are primarily needed for control, surveillance, and enforcement (CSE), while fisheries science relies on high-resolution data to support evidence-based management, assess spatial impacts, and inform MSP. The latter includes evaluating interactions with other marine activities such as offshore wind farm development, oil and gas operations, or MPA implementation. Improved resolution in scientific datasets enables better support for the fishing industry by helping to safeguard access to fishing grounds and minimize conflicts with competing marine uses. While real-time tracking remains under the remit of control agencies, alternative approaches to data trans-

mission can help balance cost, environmental impact, and utility, offering a viable trade-off for science and industry alike.

Specifically addressing SSF fisheries, Rufino et al. (2023) evaluated the changes in FE using 30 s up to 10-min time interval, associated with bivalve dredges and octopus pots and traps fisheries in Portugal, and concluded that the total area of the fishing operations decreased up to 48% if 10 min were used instead of 30 s, whereas the estimated length of the fishing operations decreased by 28%. Mendo et al. (2019a) evaluated ping rates from 1 s to 30 min in the pots and traps fishery in Scotland, and showed that increasing the position intervals from 30 s to 5 min decreased the estimated area fished per trip by ∼30% and significantly underestimated the number of hauling events conducted.

Thus, as the extent of FE underestimation depends on the behaviour of the vessels, the geometry of the fishing track, and respective sinuosity, a conservative approach with a higher resolution should be used, so that it can accurately include a plethora of métiers and fleets (Skaar et al. 2011). For SSF and passive gears, in agreement with the expert group gathered in ICES WKSFGEO (ICES 2022) and ICES WKSSFGEO2 (ICES 2023), 30 s or less polling frequency should be used. For LSF, optimal ping frequency should be further analysed in detail considering the current AIS data availability, but it should also be in the scale of minutes. Although typical bottom trawling effort of LSF could be well described using 10-min interval, there are LSF fleets operating at high speed and short fishing event such as Scottish fly shooters and pelagic seiners where fishing activity identification and estimation of gear dimension would require even higher frequency (30 s–1 min).

Methodological limitations

Tracking systems record data for the entire fishing trip, but different methods are required to classify the fisher's activity at each point (e.g. hauling, traveling, and setting), as the tracker does not record this information directly. Some gears and vessels, have been equipped with sensors to track the activity as well (https://doi.org/10.13140/RG.2.2.13561.67683), but these remain exceptions. Consequently, fishing activity typically must be inferred indirectly from parameters such as the vessel's speed at the time of polling.

The simplest methods rely on a fixed speed threshold to determine fishing activity, which can be estimated based on prior knowledge of the fishery or through statistical analysis (e.g. regresion trees, Rufino et al. 2023). More advanced approaches employ statistical (Mendo et al. 2019b, Rufino et al. 2023) and machine learning techniques, such as segmented regression (Muggeo 2003), mixture models (e.g. mixtools) (Benaglia et al. 2009), or Bayesian models (Sales Henriques et al. 2023). Samarão et al. (2025) compared several machine learning methods for classifying SSF fisheries and developed a framework to improve the predictions. However, these methods are limited by the number of data points available per fishing trip, which, in turn, depends on trip duration and polling frequency. For example, an LSF trip lasting 4–24 h with a 2-h polling interval yields only 2–12 positions, which is insufficient for most methods. While more complex approaches offer improvements over simple speed filters, all methods are ultimately constrained by the tem-

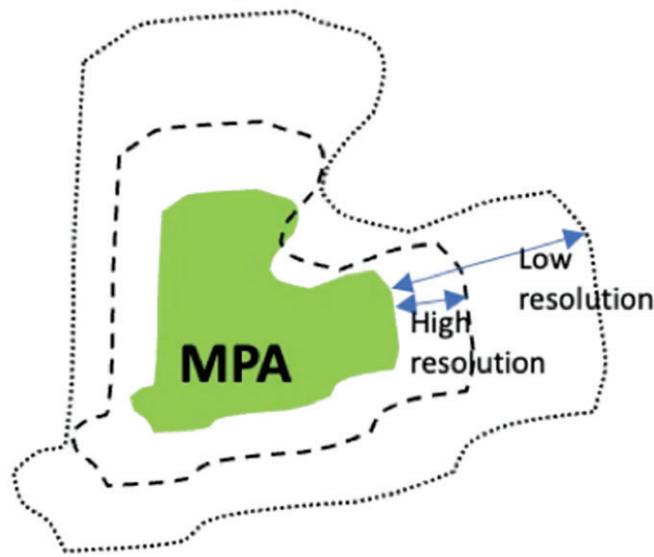# Buffer no-fish zones around protected areas

Figure 3. Example of the magnitude of the no fish areas around protected in a case of low and high resolution.

poral resolution and quality of the input data (Palmer and Demarest 2018).

Compliance with regulations

Currently, about 12% of EU seas are protected areas, but only a fraction of these have management plans, and <1% are strictly protected, including fishing bans (Kriegl et al. 2021). The EU's Marine Action Plan, adopted in 2023, commits to protecting 30% of its seas by 2030, with 10% being strictly protected (EU COM/2023/102). This involves creating many small MPAs where fishing is prohibited and special jurisdiction applies. Consequently, fishing near these zones requires compliance with legislation, and fishers must prove they are not operating inside no-take zones using geo-location data (i.e. spatio-temporal position data, identified by tracking devices).

The required buffer zone around MPAs, where fishers must demonstrate compliance, is influenced by polling interval, in fact. For instance, considering a 2-h polling interval, and a Speed Over Ground of 3.5 knots, the average speed at which vessels operate while engaged in fishing activities, it results in a 12 964-m buffer around natural reserve polygons (Fig. 3), within which fisheries cannot operate as they could not prove they were not fishing in a no-take zone. This buffer shrinks to 1 621 meters if using a 15-min interval, e.g. In the North Sea, this change in polling resolution from 2 h to 15 min would make 2 485 km^2 available for fishing. To address this, the German and Dutch governments increased ping rates from 2 h to 30 min (approximately every 3240 m) within a 5 nautical mile (10 km) alert zone around protected areas (delegated act of May 2023, EU technical regulation 2019/1241). This requires a technical setup allowing control authorities to remotely and automatically adjust the VMS ping rate in specific areas, which is not always available. If higher resolution

data were consistently available, such adjustments would be unnecessary.

However, while AIS is mandatory for fishing vessels >15 m LOA in the EU, it is also mandatory for smaller vessels fishing in the Bratten Natura 2000 area in the Swedish EEZ in the Skagerrak, where AIS is required and used similarly to VMS for compliance purposes (delegated act of 5 September 2016, EU technical regulation 2017/118).

Another example is seen in Denmark (Nielsen et al. 2021), where by using high temporal resolution trackers and detailed habitat mapping, fishers can dredge near sensitive areas, such as eelgrass habitats, without damaging them. Without these tools, the entire area would be closed to fisheries.

Additionally, courts or national authorities often require official research bodies to provide evidence of fishing activities in specific areas and periods. In these cases, the frequency of the polling interval is crucial. For example, the Swedish government has relied on a 10–30 s polling frequency, which allowed expert judgment to identify specific parts of the trawling process. This highly detailed description of a trawl event would not have been possible with polling at hourly or even 5–10 min interval.

Marine spatial planning

The increasing spatial demands of human activities at sea and the rising conflicts over marine area usage mandate integrated governance processes such as maritime or MSP (Ehler 2021). For example, activities such as offshore wind farms, aquaculture, artificial reefs, submarine communication cables, marine scientific research, oil and gas industry, deep-sea mining, and historical dumping of radioactive waste and munitions significantly impact the seafloor (Benn et al. 2010). Additionally, protected and no-take areas that aim to conserve species, ecosystems, and fishing stocks, also compete for ocean space. The management of all these stakeholder's demands, requires MSP prioritization strategies, for which the temporal resolution of the FE is crucial (Ardron et al. 2008, Degnbol and Wilson 2008). Further, legislated fishing closures of some areas, imply a redistribution of FE, which should be properly predicted (Hogg et al. 2024) as well as prioritizing areas for protecting specific groups, such as sharks and marine mammals (see the section below) (Maioli et al. 2023).

Accurate habitat mapping using high-resolution data enables better identification of critical areas needing protection and more robust assessment of anthropogenic impacts. For example, cumulative maerl beds surface area (seaweeds) overlap with commercial activity increased from 50 to 200 m grid cell length and declined at resolutions coarser than 500 m, indicating a strong bias associated with spatial resolution, which is a direct consequence of the temporal resolution used to estimate the FE (Riley et al. 2024).

Further, combining the spatial footprint of human activities, such as FE (Benn et al. 2010), with species distribution models and economic analyses (Stelzenmüller et al. 2015) helps understand how habitat vulnerability might shift due to climate change (Marshall et al. 2014). These models can identify potential synergistic cumulative impacts, allowing for a precautionary approach. For instance, combining global habitat suitability predictions with FE maps can identify areas where key species are threatened by human activities, and thus, address both spatial and temporal vulnerabilities. Additionally, high-

resolution FE distribution patterns can improve spatial interpolation of seabed substrates (van der Reijden et al. 2023), enhancing habitat mapping.

Thus, high-resolution FE maps facilitate directing conservation efforts where needed, assessing risks, selecting priority areas for conservation and fishing, as well as addressing the needs of different stakeholders, and potentially reducing the overall costs. Note, however, this consequence can be considered to be nested within consequence 1 and 2.

Impact on the seabed

The assessment of trawling impacts on seabed habitats depends strongly on the resolution of input data (Piet and Quirijns 2009, Roland Pitcher et al. 2022, Hiddink et al. 2023), even when only spatial or impact indicators are considered (Piet and Hintzen 2012, Rufino et al. 2019), High-resolution habitat maps and detailed estimates of FE lead to more robust and typically more conservative impact evaluation. For example, coarser resolution data dilutes FE over larger areas (larger grid size), smoothing out peaks in fishing intensity. Consequently, coarse resolution data can make heavily fished small habitats appear similar to adjacent unfished habitats (Hiddink et al. 2023).

Furthermore, the proportion of the fished area increases significantly with larger cell sizes (Piet et al. 2007, Amoroso et al. 2018). The overall impact of fishing is determined by both the extent of the area covered by the gear and its intensity, as each additional pass of the gear increases the respective impact on the habitat (Piet and Hintzen 2012). For example, Lambert et al. (2014) demonstrated that seabed impact area increased by 18% when using a 30-min interpolated ping rate instead of 10 min. Thus, low temporal resolution, resulting in coarser grids with larger cells, exaggerates the extent and impact of fishing areas.

Another important aspect is that local and regional studies using vessel logbooks, plotter data analyses, overflight data, or direct tracking show that trawling distributions are often highly aggregated. However, coverage is insufficient to map total trawling distributions at the shelf sea scale (Amoroso et al. 2018).

Although generally SSF are considered low-impact fisheries, if operating in sensitive habitats, this might not be the case. While bottom contact gears like trawls and dredges are typically associated with larger seabed impact, other gears like trammel nets, gill nets, pots, and traps used by SSF (passive gears) can also significantly impact the sea floor. Silvestrini et al. (2024) estimated that over 84 000 algal shoots of *Posidonia oceanica* are potentially extirpated annually by SSF nets and traps in an Italian MPA. Their review also highlights the necessity of high-resolution FE and habitat mapping for accurate SSF impact estimates. As mentioned before, maerl beds (Riley et al. 2024) and eelgrass habitats (Nielsen et al. 2021) also require highest vessel tracking resolution to make compromises and permit fishing activities in those areas. Note, however, that this consequence can be considered to be part of consequence 1 and 2 or a direct consequence of it.

By-catch of sensitive species and VME

Understanding the magnitude and locations of potential negative ecosystem impacts from anthropogenic pressures is critical for predator conservation and management. Accurate FE maps are essential to detect overlaps between fishing vessel ac-

tivity and top marine predators, including sharks, tunas, mammals, seabirds, and critically endangered leatherback turtles (Hogg et al. 2024, Welch et al. 2024)

For instance, marine mammal distribution data combined with GPS loggers have been used to calculate spatial overlap and the probability of co-occurrence between SSF and marine mammals in the Eastern Mediterranean (Glarou et al. 2022). High-risk areas for bycatch of threatened species, such as chondrichthyans (sharks, rays, skates, and chimaeras), have been identified by overlaying FE estimates with species distribution data from independent surveys in the western Adriatic Sea (Maioli et al. 2023).

In another study, a spatial risk assessment tool was developed in South Georgia using FE layers to assess high-probability areas for bycatch, potential damage to vulnerable marine ecosystems (VME), and interactions with whales and seabirds (Hogg et al. 2024). This tool also accounts for the displacement of FE due to fisheries restrictions, providing valuable scenarios for managers and stakeholders. However, the effectiveness of such tools relies heavily on the accuracy of FE maps, which depend on their temporal resolution.

Recent approaches suggest using onboard cameras and deep learning image analysis to record bycatch of sensitive species. When combined with high-resolution trackers, these methods can identify highly sensitive areas for potential temporal fishing closures. Such management strategies also require high-resolution FE data across entire fleets or métiers to accurately predict potential encounters and areas needing protection. Note, however, that this consequence can be considered to be a consequence of consequence 1 and 2.

Geographic projections

FE indicators are often summarized into spatial grids to create maps, commonly using C-squares with a resolution of 0.05°. This geocoding system creates unique cell identifiers for a regular square grid based on an unprojected coordinate system. However, because C-squares are not an equal-area grid and not based on a metric projected system, the size and area of a C-square vary with latitude. Consequently, a C-square in southern Europe covers a larger area than one in northern Europe. This means that, with lower FE resolution, the probability of having at least one fishing point is higher in southern areas than in northern areas due to the larger C-square area. The opposite pattern emerges when considering common FE indicators for bottom trawl fisheries, such as the Swept Area Ratio. As the resolution of FE data increases, the geographic effect's magnitude diminishes (Fig. 4).

To illustrate the impact of varying cell sizes, consider a hypothetical fishing trip of a vessel traveling at an average speed of 3.5 knots, with a polling frequency of one hour, and a swept area of 0.65 km² (1 h x 6500 m/s x 100 m = 0.65 km²), represented by 10 points. This fishing trip's impact would differ significantly if it occurred at latitude positions in North Africa, Northern France, or above Iceland (Fig. 4).

Bias in stock assessment models

Spatial variation and connectivity are key drivers of population dynamics and sustainable harvest levels (Beverton 1957). Many fisheries rely on Catch Per Unit of Effort (CPUE) to monitor stocks in the absence of direct population abundance estimates (Walker and Bez 2010). CPUE is used to indicate abundance, assuming fishing behaviour is consistent
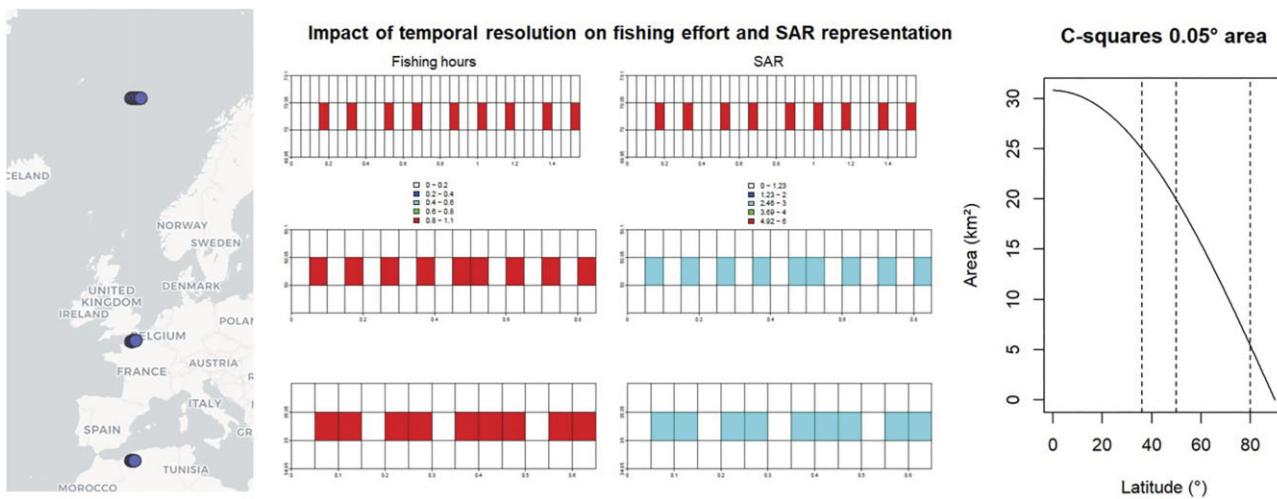
Figure 4. Effect of geographical projection on the mesh size used to represent FE indicators and related consequences on the values of these variables.

over space and time. However, landings, effort, and CPUE often exhibit strong spatial patterns (Maunder et al. 2020), thus requiring CPUE standardization.

Indices of abundance based on CPUE are crucial for calibrating stock assessment models. Standardizing CPUE involves spatial considerations, such as incorporating year-area interactions as a random effect (Hoyle et al. 2024), to account for spatiotemporal dependencies. Failing to consider these dependencies in CPUE standardization can introduce biases that affect the accuracy of stock assessment models (Fuster-Alonso et al. 2024). Information on FE, such as VMS data, enables CPUE standardization by considering spatiotemporal factors and variables such as depth and fishing area (Watson et al. 2018).

However, the effectiveness of FE metrics depends on the resolution of boat position data relative to the duration of fishing operations or trips (Katara and Silva 2017). Low resolution may prevent accurate quantification of spatial dependence in FE, leading to biased CPUE and incorrect variance estimates due to under sampled time-area cells. This undetermined uncertainty and bias in CPUE can propagate through stock assessment models, compromising the accuracy of state and reference point estimates (Soto et al. 2023).

Conclusion

High-resolution tracking data significantly enhances policy and decision-making by providing detailed and accurate information. However, its acquisition and processing present several challenges, including high implementation costs, the need for advanced technical expertise, gaps in data availability, and most importantly, collaboration and support of the fishing industry (Riley et al. 2024). These limitations can result in uneven monitoring across fleets, reduced accuracy in effort estimation, and potential biases in fisheries management decisions, among other aspects analysed in the current work.

Despite these challenges, recent technological advancements have decreased costs and increased accessibility of tracking systems and analysis. The trade-off between upfront investment and improved data quality must be weighed against the long-term consequences of inadequate monitoring,

such as misinformed policies, reduced regulatory compliance, and the risk of overexploitation.

We argue, based on the scientific evidence summarized in this work, that high-temporal resolution tracking data for EU fishing fleets should be collected, regardless of vessel size or gear type. For SSF and passive gears, there is an increasing amount of evidence that tracking should be conducted with at least a 30-s polling frequency as a conservative approach. For LSF using active gears, further work is required to determine the optimal ping frequency, but overall, it should be on the scale of a few minutes, depending on the gear used. Given that satellite transmission cost may hinder increasing ping frequency in the European region, it is important to clarify that real-time data transmission is not necessarily required. Most if not all applications, including also compliance is done on 'historical data'. In a European context a VMS system for real-time monitoring could be combined with an MTS where high frequency track data is transmitted/uploaded after the fishing trip. The absence of such resolution can impose substantial indirect costs on stakeholders, including lost economic opportunities (e.g. restricted access to fishing grounds, exclusion from MSP) and weakened governance. Therefore, future legislation should explicitly define the required temporal resolution for vessel tracking (e.g. time intervals) and promote consistent implementation across Member States. These steps are essential to ensure equity, transparency, and sustainability in fisheries management. We hope this work raises awareness among decision makers about the substantial costs to stakeholders of not implementing and enforcing such systems through legislation.

Author contributions

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Russo: Writing—review and editing; Vanessa Stelzenmüller: Writing—review and editing; Miguel Gaspar: Writing—review and editing; Jose Rodríguez-Gutiérrez: Writing—review and editing; Daniel C. Fernández: Writing—review and editing; María S. Ruiz: Writing—review and editing; Josefine Egekvist: Writing—review and editing; Julien Rodriguez: Writing—review and editing, Visualization; Roi Martinez: Writing—review and editing, Visualization; Christian von Dorrien: Writing—review and editing; Patrik Jonsson: Writing—review and editing; Maria Mateo: Writing—review and editing; Torsten Schulze: Writing—review and editing; Tania Mendo: Writing—review and editing.

Supplementary data

Supplementary data is available at *ICES Journal of Marine Science* online.

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Data availability

The data underlying this article cannot be shared publicly due to confidentiality of fisheries data. The data will be shared on reasonable request to the corresponding author.

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