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Mission planning for autonomous systems integrating socio-technical-ecological risks

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The ocean remains one of Earth's most under-sampled environments, creating a gap between societal demands for ocean knowledge and the limits of costly, infrequent, human-dependent ship and in-situ observations. A potential solution is robotic organizations, i.e., heterogeneous teams of sensing platforms capable of real-time, adaptive, and intelligent data collection that operate safely and efficiently with minimal human presence. This requires integrated systems-of-systems capabilities beyond single robotic platforms. Key challenges include robust collaboration and resilience during long-duration missions in remote, harsh settings, and the integration of domain knowledge about ecosystem dynamics, human legacies, and ocean infrastructure into autonomous reasoning and decision-making. This paper characterizes socio-technical-ecological mission risks associated with ocean robotic organizations and proposes a conceptual approach to mission planning for risk-aware autonomy. Central to the approach is supervisory risk control with online risk models distributed across edge and cloud computing domains, enabling safe robotic interaction under limited underwater communications. We outline how risk models inform adaptive sensing and control, and guide cooperative behaviours. These developments are decisive for achieving scalable, intelligent, and resilient ocean robotic operations and organizations while improving observation quality.

Keywords: Mission planning, Autonomous systems, Robotics, Artificial intelligence (AI), Supervisory risk control (SRC), Decision-support, Socio-technical-ecological, Risks.

1. Introduction

The ocean is one of the most under-sampled environments on Earth because of its vastness and opacity limiting most remote sensing modalities and, therefore, our ability to observe processes at the temporal and spatial scales required for science, industry, and policy (Reigstad et al. 2025). Traditional ship-based and in-situ observations are scientifically valuable, but costly, infrequent and heavily reliant on human intervention. As a result, there is a mismatch between societal demands for ocean knowledge and current observation system capabilities.

Robotic platforms, such as autonomous underwater vehicles (AUVs), autonomous surface vehicles (ASVs), remotely operated vehicles (ROVs), uncrewed arial vehicles (UAVs), are advancing individually, but achieving high-quality observations and true autonomy in unstructured ocean environments demands integrated mission capabilities that transcend the limitations of single systems. Some large-scale fleets of underwater robots already exist in the form of profiling floats and underwater gliders. The Argo program comprises ~4,000 profiling floats that collectively deliver global, sustained, near-real-time observations, operating under highly standardized rules with no coordination, yet achieving reliable global coverage (Roemmich et al. 2019). Similarly, underwater glider networks operate as loosely coupled fleets executing pre-planned transects, relying on shore-side supervision and delayed data assimilation (Testor et al. 2019). These systems can be seen as minimal robotic organizations, where risk is managed implicitly with conservative vehicle behavior, redundancy, and operational protocols rather than holistic risk-aware planning or multi-agent coordination.

Emerging heterogeneous robotic operations, such as the "observation pyramid" concept, which is an integrated network of ocean platforms from seabed to space (moorings, AUVs, ROVs , USVs, UAVs, satellites), demonstrate the value of multi-modal sensing (Ludvigsen and Johnsen 2025). Still, in practice, remote and in-situ sensing remain loosely coupled, they rely heavily on pre-mission planning and human oversight and thus struggle to adapt in real time to emerging risks and opportunities (Williamson et al. 2023; Fragoso et al. 2024). Achieving autonomous robotic organizations will require a step-wise progression from simple interactions and hierarchies to self-reconfiguring structures with adaptive behavior (Skaugset et al. 2025). The operational complexity and risk, are, however, significant (Ludvigsen, 2021; 2025; Yang et al. 2022), motivating real-time risk models on the edge (onboard) and in the cloud (network/centralized) that interface with digital twins and onboard autonomy, despite severe underwater communication constraints. From a safety and reliability perspective, the central challenge is to enable systems-of-systems cooperation that is robust to mission uncertainties and deviations, while remaining verifiable and controllable over long-duration operations in harsh environments. This calls for explicit modeling of mission and system risks while also considering ecosystem dynamics, human activity and legacies, and ocean infrastructure integrity at unprecedented spatial and temporal scales. This risk knowledge needs to be embedded into autonomous reasoning, artificial intelligence (AI), and decision-making processes.

Therefore, the objective of this paper is to propose a conceptual approach for risk-aware mission planning, with emphasis on socio-technical-ecological risks associated with deploying robotic organizations in the ocean. We outline the role of online risk models informing supervisory control (SRC), operating both on the edge and in a network that can interact with autonomous systems despite limited and intermittent underwater communications. These developments are decisive for achieving scalable, intelligent, and resilient ocean robotic operations. The proposed concept is based on literature studies and the co-authors´ extensive experience over several decades with field robotic operations all over the world.

The remainder of the paper is organized as follows: Sect. 2 introduces mission planning for robotic organizations. Sect. 3-4 presents a risk taxonomy, and the novel mission planning approach. Sect. 5 showcases an example, Sect. 6 discusses its feasibility and further research needs, before Sect. 7 provides the conclusions.

2. State-of-the-art

2.1. *Mission planning*

Planning an autonomous mission begins with specifying clear objectives and parameters for the operation. A mission plan, e.g., for an AUV, specifies locations and waypoints, depths, transit speeds, and payload settings, chosen by operators and scientists related to the vehicle´s operational limits, such as range, depth rating, speed, energy capacity, as well as anticipated conditions, including bathymetry, currents, and temperature. Contingencies, such as energy shortfalls, payload faults and failures, obstacle detection, leak alarms, battery anomalies, and navigation errors may override the nominal plan. Since underwater communications are limited, an AUV has to rely on predefined emergency behaviours allowing operators to trigger alternative plans with minimal data exchange.

Mission planning also includes planning (replanning) during operation. A major challenge is to select when and where to sample, addressing time and space considerations. A conventional lawnmower pattern can be feasible for seabed mapping, but is less efficient when features are non-uniform, such as for fronts, eddies, phytoplankton blooms, and zooplankton layers. Ocean fronts, for example, are boundaries between distinct water masses (differences in bio-geo-chemistry) characterized by strong physical gradients, and efficient mapping requires the vehicle to follow these boundary curves, which predetermined fixed plans cannot ensure (Ludvigsen et al. 2025). Adaptive missions adjust the vehicle´s path based on real-time measurements during operation.

Mapping the dynamic ocean features benefits substantially from collaboration between heterogeneous robots with different operational capabilities. Communication, coordination, and deliberate task sharing improve sampling efficiency and spatial coverage. Deploying multiple vehicles improves sampling and spatial coverage, but requires communication, coordination, and deliberate task sharing. Mission planning becomes especially important for multi-vehicle operations typical of robotic organizations since complexity increases, with potentially longer duration and more coordination needs.

Coordination can be centralized or distributed. Centralized coordination relies on a globally optimal plan using network-wide information. A challenge is that such a scheme is vulnerable for communication outages and single-point failures at the coordinating node, it also tends to require high bandwidth, low-latency communications which are rarely available underwater. Distributed approaches, on the other hand, allow each individual robotic vehicle to broadcast its state, objectives, and observations and to plan locally based on shared summaries. Although local planning may sacrifice some optimality, decentralized coordination is generally more resilient to packet loss and node failures and is thus often preferred in marine science. A network of cooperating robots or agents can close critical observation gaps by dividing the search space, while maintaining formations relative to dynamic gradients, and revising sampling patterns when new information is available. To facilitate coordination and situation awarenesses in the network, updates can be shared close to real-time by satellite when access to surface is feasible (Ludvigsen et al. 2025).

2.2. Supervisory risk control in mission planning

SRC is the ability of a robot to make risk-informed decisions (Utne et al. 2020). Specifically, a risk model is implemented into the guidance/mission planning layer of the autonomous system to provide holistic risk awareness for the robot or autonomous system during operation. A control system may utilize risk information in different ways, such as directly from a risk model (e.g., a Bayesian belief network (BBN)), as decision or optimization criteria, as a constraint or for modifying a constraint, or embedded into risk maps for path planning (Thieme et al. 2021).

Existing SRC for different applications are mainly focused on individual vehicles, e.g., (Johansen and Utne 2024; Bremnes et al. 2025; Rothmund et al. 2025). A main difference between the SRC framework and other approaches for autonomous vehicles is that the former aims to capture a holistic risk spectrum related to a mission, whereas the latter most often are focused on a few risk factors, e.g., collision risk in terms of closest point of approach and time to collision (CPA/TCPA) (Vagale et al. 2021). With the emerging robotic organizations and the corresponding increase in operational complexities, the need for including a holistic risk spectrum enabling risk-aware autonomy, becomes even more decisive.

Planning and replanning involves optimizing information value, so that the robotic vehicles can be directed to the most mission valuable locations. For a robotic organization, it is necessary to consider which vehicles are most feasible to use for different locations, depending on operational capabilities. A typical approach for the marine environment is the application of a risk/reward utility function that weighs the desire to investigate unknown areas against the benefit of sampling areas that, on the basis of prior knowledge, are expected to have interesting features. Thus the utility function balances exploring new areas with exploiting what is already known (risk/reward). SRC may provide risk estimations to be used by a utility function. An early concept is demonstrated in (Bremnes et al. 2020) for the behaviour of an AUV where mission utility is maximized subject to a risk constraint.

A risk model in SRC runs online and utilizes sensor measurements and contextual information to identify potential hazards, assess and mitigate risks during a mission. Contextual information in ocean missions are related to operational conditions and location, mission extent and duration, human supervisor-autonomy interactions, and the technical health of the vehicles involved. Such information is necessary to generate holistic risk awareness, capturing a combination of socio-technical and ecological hazards and risks.

3. Socio-technical-ecological risks for robotic organizations

During a mission, the following potential negative impacts or consequences may be relevant to mitigate, which must be considered in both mission planning and replanning:

- Damage to own vehicle(s)
- Damage to other vehicles/robots
- Damage to seabed/environment
- Damage to third-party assets
- Damage to human legacy sites
- Damage to ecosystems and habitats
- Negative interference/impact on ecosystem
- Loss of biodiversity (biomass & production)
- Unsafe vehicle manoeuvres
- Human fatality/injury
- Violations of relevant regulations
- Geopolitical tension

These negative impacts must be balanced against the objective and purpose of the mission. Determining risk acceptance criteria or similar thresholds will provide guidance on how much risk the human supervisor(s) is willing to take to achieve the mission goals. During operation, such criteria may be closely connected to the vehicle´s operational envelope and safety constraints, and therefore they may need to shift dynamically.

To mitigate relevant negative impacts during a mission, it is necessary to identify potential hazards and hazardous events that may occur. These need to be identified both for pre-mission planning and SRC. During a mission new information will provide updates regarding the presence and likelihood of hazards and risk scenarios. The taxonomy in Table 1 shows important technical, environmental, human, ecological and security hazards which often may be fragmented and considered separately (Jones et al. 2025). Hazards across ocean domains need to be considered systematically and holistically for mission planning. The main novelty in this taxonomy is related to the inclusion of socio-technical-ecological hazards, and interaction hazards of relevance to robotic organizations.

4. A mission planning conceptual approach for risk -aware autonomous systems

Figure 1 shows the proposed mission planning approach for a robotic organization and covers both centralized and decentralized coordination. The probability of finding a mission´s target feature is calculated from prior information, statistical knowledge of their characteristics, and data acquired during the mission. Data assimilation techniques are used to update the vehicle´s world model. The world model is a computational representation of the robotic operating environment, so that decisions are based on the latest state and uncertainties.

The cycle in Figure 1 includes several phases, where risk assessment plays an important role. In the planning phase, the best available world model, numerical models, remote sensing and other auxiliary data, and algorithms are used to optimize ocean sampling. Then, the vehicle executes the plan and moves towards the sampling location. Onboard instruments measure and sample, collect data on the feature of interest (e.g., temperature, salinity, plankton concentration). Lastly in the cycle, the information gathered in the preceding step is used to update the world model.

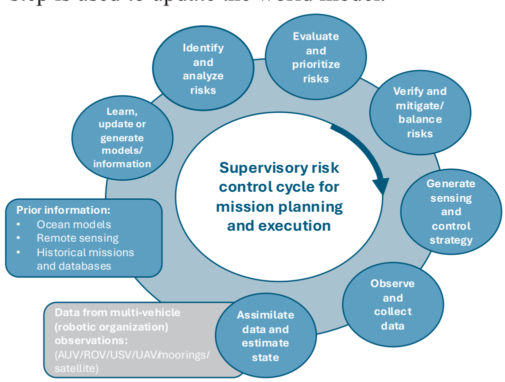

Figure 1. Mission planning approach for robotic organizations. Further developed from (Ludvigsen and Johnsen 2025; Utne et al. 2025).

Table 1. Taxonomy including socio-technical-ecological hazards for missions with robotic organizations. Adapted from (Utne et al. 2014) and further extended with knowledge from NTNU robotic labs (AUR-lab, UAV – lab).

Hazard category	Hazard/hazardous event	More detailed information
Vehicle hazards	Power failure	Battery system failure
	Structural failure	Pressure vessel leaks
	Buoyancy system failure	Pressure vessel leaks
	Propulsion system failure	Thruster/rotor/propeller failure Jet system failure (if applicable)
	Software failure	Control system failure Electronics hardware failure Tether failure (if applicable) Sensor system failure
	Navigation system failure	Bad GPS Loss of contact with external system Wrong/insufficient path & trajectory replanning failure
	Sensor system failure	Sonar failure Failure in transponders/beacons Failure in beam Camera failure Lights failure
	Collision	Collision with seabed or subsea structure Collision with ship/airplane Collision with obstacle
	Grounding	Grounding with shore or obstacle
	Communication failure	Acoustic interference Tether failure (if applicable) Tether entanglement (if applicable)
	Charging failure	Electrical faults and failures
	Payload system failure	Insufficient mapping/path & trajectory planning Sensor failure
Robotic interaction hazards	Collision	Collision with another vehicle/robot Undesirable wind, sea state, currents, turbidity, fog Path planning overlaps
	Communication failure	Loss of communication betw. vehicles/human operator Delayed communication Interference Undesirable wind, sea state, currents, turbidity, fog
	Common cause failure	Technical failures, maloperation
	Navigation failure	Bad GPS Spoofing Hacking
	Inefficient mapping	Path & trajectory planning overlaps Mapping inaccuracies Positioning and localization inaccuracies
	Weather/sea state	External communication failure
Human supervisor hazards	Negligent	Operation outside the vehicle´s design envelope
	Inexperience/lack of training	Insufficient situation awareness, human error
	Deficient safety climate	Inadequate focus on risk management Inadequate communication Human fatigue Work task overload Deficient mission planning and change management
External hazards	Strong wind	Navigation error in external positioning system
	Strong currents and tides	Navigation error in local positioning system
	Low visibility	
	Temperature	Extremely high/low temperatures
	Salinity	Technical failures
	Sea spray	Icing/technical failures
	Icebergs	Collision/mission delays/failure/damage
	Multi-year ice	Collision/mission delays/failure/damage
	Ice based seabed changes	Collision/grounding
	Earthquake/tsunami	
	Seabed characteristics	Unexpected terrain for path planning/replanning Challenges for optimizing mission performance Stirred particles leading to low turbidity
	Water depth/altitude	Tether failure due to associated drag (if applicable)
	Hydrocarbons/electromagnetic field	Non-compliance with safety zones, e.g., oil/gas, high electric voltage etc. Presence of shipwrecks (PPW) or other man-made objects
	Explosives	Remnants of war (ERW)
	Entanglement	Vehicle gets stuck in obstacle, debris etc.
Ecological hazards	Pollution	Release of dangerous chemicals, debris, light or sound Spreading of non-invasive species
	Disturbance	Failure of safe distance to organisms Disturbance of wildlife Wildlife deaths
	Ecosystem regulation violation	Non-compliance with sustainability resource management
	Wrong timing	Mission is performed too early/late to capture essential ecosystem knowledge
	Wrong site	Mission is performed in wrong location not capturing essential ecosystem knowledge
Security hazards and threats	Sabotage	
	Espionage	

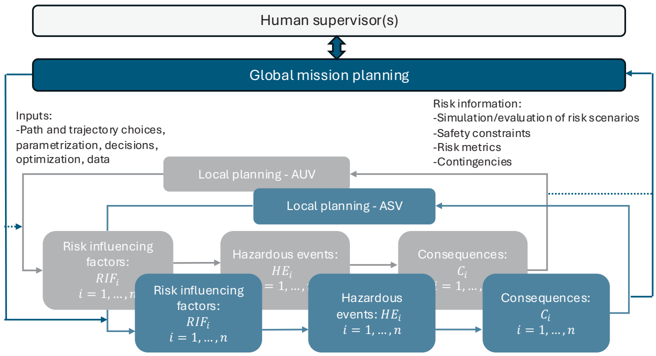

Figure 2. Online risk modelling and interaction with mission planning for the AUV and ASV (robotic organization).

The proposed mission planning approach provides risk-aware autonomy as it identifies, evaluates, mitigates and manages risk while generating sensing and control strategy and making risk informed decisions, as shown in Figure 1. Risk-awareness contributes to robotic resilience, enabling a robot to prevent, mitigate, or handle anomalies and failures by smoothly scaling down its performance, adapting its behaviour, and recovering its situation awareness.

5. Example – mission planning for risk – aware heterogeneous robotic operation

To illustrate the proposed concept, a mission with an ASV and an AUV inspecting a potentially polluting wreck (PPW) is briefly exemplified with main focus on the risk identification and modelling contribution. In recent years, the focus has increased on marine explosive remnants of war (ERW) (GICHD 2025) and PPW (Brennan 2024; Achterberg et al. 2025). These represent critical socio-technical-ecological hazards that demand risk-aware autonomy for detection, documentation and monitoring, if a robotic system is to be trusted to handle the task unsupervised. The ASV transmits acoustic signals to the AUV to update its estimated position, to limit navigational drift and communicate relevant data to/from human supervisors. This means that the ASV is required to follow the AUV within a specific range (see, e.g., Bremnes et al. 2024; Kristensen et al. 2025). The taxonomy in Table 1 can be used as a starting point for identifying what can go wrong during the different operational phases, such as pre-mission planning and preparations, deployment, survey, close-up inspection, communication with shore/operators, vehicle retrieval, and payload data processing after mission. These phases involve different hazards and hazardous events, which means that a risk model for an AUV may not be identical to a risk model for an ASV. Relevant hazards/risk influencing factors (RIFs), hazardous events, and consequences can be selected from the taxonomy and structured into the online risk models, in line with the bow-tie risk model (Rausand and Haugen 2020), and shown in a simplified version in Figure 2. Here, the local online risk models onboard the vehicles communicate with a "global" mission planning node for the robotic organization, potentially also involving human supervisors. Safe and efficient vehicle interaction also requires addressing human-autonomy collaboration and task-sharing, which face hazards such as communication failure (Table 1).

In the planning phase, an online risk model on the edge interacts with the robot´s world model and other data. The risk model needs to be developed based on a risk analysis, e.g., using Table 1 in a HAZID or systems-theoretic process analysis (STPA) before operationalization and quantification of the relevant hazards and RIFs.

When socio-technical-ecological hazards are included holistically in an online risk model, it will inform the supervisory (mission) control with more accurate and complete information about risks, e.g., not only about technical integrity risks related to the AUV, but also related to the PPW (e.g., potential pollution), the surrounding ecosystem (e.g., vulnerable species/habitats), and the human supervisor (e.g., loss of communication, workload). Relevant methodologies for online risk models can be BBN, fault trees, event trees, as well as Markov modelling can be used, preferably in combination with simulation and digital twins. During the mission, the ASV and AUV execute their plans and their onboard instruments measure and sample the data related to the PPW (e.g., presence and concentration of toxic chemicals/oil pollution/target elements in water and sediment, structural integrity and state of degradation). The information collected is used iteratively and continuously to update the risk and world models to ensure safety and achieve mission success.

6. Discussion

6.1. *Feasibility of the proposed mission planning approach*

Risk assessment is the foundation for the development of risk models which can estimate the risk during a mission, both for the individual vehicles (edge/distributed), as well as the entire mission (globally/centralized). The risk information provides guidance to the control systems of the AUV and ASV; thus influencing their behaviours. Currently, autonomous systems are not risk-aware, as they are only using one or a few risk factors, e.g., as safety constraints.

In the proposed approach, a more holistic and systematic approach is outlined. This systematic approach is particularly important for large-scale operations: as heterogeneous robotic organizations grow to include many vehicles with task-specific sensors, our holistic methodology becomes essential for maintaining safety and mission success.

Machine learning methods may be feasible for complementing the risk models for diagnostics and learning, but the overall mission planning approach uses methods and models from risk science contributing to transparency and explainability in AI. Risk assessment is clearly vital for safe and robust design of vehicles, and for preplanning of missions, but currently there is less focus on risk-awareness and holistic risk models informing decision-making during a mission. An increased focus is necessary to achieve risk-aware and resilient autonomous systems, improving ocean observation, and other autonomy application areas.

Adaptive sampling has shown potential for improving the efficiency and scientific outcomes in ocean monitoring (Mo-Bjørkelund et al. 2024), but current spatial-temporal models do not fully account for the many factors that influence mission risk, especially for robotic organizations with heterogeneous platforms working with limited communication, and in uncertain environments. A key step to achieving risk-awareness is implementing contextual information enabling robotic organizations to detect hazards, balance safety, data quality, and endurance, and adjust plans together in real time to achieve mission goals. For ocean robotics this means that interdisciplinary knowledge is needed, such as from marine ecology, human legacies, risk science and robotics, embedded directly into robotic control systems and decision-making.

6.2. *Future research needs*

To move forward and improve ocean observation, there is a need for interdisciplinary research across risk science, robotics, AI, and ocean domains, such as marine ecology and human legacy studies. The ocean domains, on one hand, provide important contextual knowledge, e. g, about changes in biodiversity, health state, production, pollution, and infrastructure anomalies at different time and spatial, scales and their potential causes and consequences. On the other hand, the ocean provides "disturbances" and "hazards" related to an unforgiving, variable and often high-energy environment (e.g., currents, waves, pressure, corrosion, biofouling, limited sensing and communication range). Risk science structures and transforms relevant contextual knowledge into risk models. Robotics and AI can transform the fragmented ocean data, as well as the risk information, into baselines and machine readable models, supporting real-time robotic perception and data processing pipelines into reasoning, decision-making and mission adaptation. A research gap that challenges risk science in particular is determining risk acceptance or tolerability in missions, balancing complexity in the risk models, and developing solutions for risk aggregations and trade-offs, both in local and global mission planning.

7. Conclusions

This paper proposes a concept for a novel mission planning approach that embeds socio-technical-ecological hazards and risks directly into robotic control systems, enabling risk-aware and resilient autonomy. Our proposed approach includes systematic risk assessment that utilizes and transforms ocean observation data for real-time planning and adaptive decision-making for heterogeneous ocean robotic organizations. Explicitly mapping and connecting socio-technical-ecological hazards to the development of online risk models as part of SRC, can contribute to proactive, risk-aware autonomy, providing a foundation for persistent, trustworthy ocean operations. Although the concept of robotic organizations has been briefly demonstrated, more research is needed to fully realize the potential of such systems-of-systems. These developments are decisive for achieving scalable, intelligent, and resilient ocean observation with high quality data and knowledge.

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