A Statistical Approach to Surface SAR Fleet Distribution Optimization: A Case Study of Croatian Waters

Nina Kostović[1], Ivan Toman[1] Pero Vidan[2]

The objective of this research paper is to propose a novel approach to the spatial distribution of the surface Search and Rescue (SAR) units in Croatian territorial waters using the A* algorithm. The developed model identifies the shortest route between maritime accident sites and the proposed locations of SAR facilities. Croatian waters, dotted with scattered small islands and frequent summer maritime accidents, were used as a case study for model testing. Based on the specified parameters and operational requirements, the study suggests 35 optimal locations for the surface SAR fleet within the area of responsibility of the Croatian SAR service, considering the limitations discussed in the study. The aim of this paper is not to present a comprehensive solution involving multiple subsystems (surface, aerial, and surveillance units). Instead, its focus is surface search as the initial approach. This method for determining surface SAR unit distribution is not restricted to a specific area, making it suitable for various locations worldwide.

KEYWORDS

~ Surface SAR fleet distribution
~ Pathfinding algorithms
~ A* search algorithm
~ Maritime accidents

[1] University of Zadar, Maritime Department, Zadar, Croatia
[2] University of Split, Faculty of Maritime Studies, Split, Croatia
e-mail: nkostovic@unizd.hr
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1. INTRODUCTION

The vision and mission of every search and rescue organisation involve 24-hour vigilance, 365 days a year, in order to rescue distressed individuals within the shortest possible time frame (the so-called golden hour). Continuous standby, modernised maritime and aerial resources, and the formation of an integrated response system are the strategic objectives of the Search and Rescue (SAR) organization and the SAR Convention.

The eastern Adriatic coast is predominantly under the jurisdiction of the Republic of Croatia. This region's relief and geographical features emphasise its complexity, characterised by numerous islands, bays, beaches, and shores. The vast waters, the natural characteristics of the sea (such as colour and temperature), favourable climate, and the area's rich historical and cultural heritage, make it suitable for leisure craft activities, thus, significantly bolstering nautical tourism. Consequently, this segment of tourism experienced rapid growth. The Croatian charter fleet, comprising over 4,300 units (Luković et al., 2021), contributes significantly to the sector. A noticeable increase in the number of foreign yachts and boats is accompanied by an increasing number of residence permits issued for these vessels (MMPI, 2024). Toman et al. (2020) indicate that as the number and concentration of vessels in maritime traffic increase, so does the frequency of accidents. This trend was observed over the past several years and is anticipated to keep increasing. According to the maritime accident database of the Croatian Maritime Rescue Coordination Centre (MRCC), the most frequent type of accidents are those requiring medical intervention.

For effective SAR operations, the strategic positioning of maritime surface SAR units in the proximity of the accident site is crucial. Given the constraints posed by the limited availability of such units, optimising their distribution presents a significant challenge. Despite the relevance of this issue, there is a notable absence of a scientific approach adapted to the specific characteristics of Croatian waters. This study partially addresses this gap and represents the first effort to systematically analyse and propose a model for a potential solution to the issue of optimal deployment of maritime surface SAR units in this region.

The problem of SAR equipment placement optimisation is complex; various factors must be analysed for the complete solution. It is important to emphasise that the completed model that optimises SAR unit distribution must include all subsystems of the involved technologies, including surface units (vessels), surveillance and search aerial units like airplanes and drones, aerial units for search and rescue tasks like helicopters, as well as ground-based surveillance-only units and technology, for example, radars, cameras, and other related equipment. This point of view is well supported in several papers discussed in the literature review section. This paper does not aim to create a final solution. It focuses on a small subsection of the system and pertains to surface search and rescue units, i.e. vessels. As such, it can be viewed as a starting point for further research on the subject.

The primary challenge in trying to optimise the distribution of the surface SAR fleet is comprehending and interpreting the relationship between the spatial frequency of maritime accidents and the practicality of pre-allocating surface SAR units in their proximity. To effectively address this challenge, adopting a statistical approach to comprehend the geographical distribution of accidents is usually the initial step. Therefore, developing and applying sophisticated algorithms is essential for determining the most effective proximity, particularly given the limited number of available units.

The objective of such a study is the optimal spatial distribution of the surface SAR fleet, whereas the primary goal is to shorten the average response time to maritime accidents. Apart from following this research framework, the authors applied several other constraints while developing their approach. The surface SAR fleet should be stationed at locations where it can be permanently moored, and the crew can be ready to sail quickly. Therefore, a specific site infrastructure should be available, and that condition becomes an important constraint when deciding which surface SAR fleet distributions to include in the algorithm. Upon hand-picking locations that meet the above conditions, the authors utilised the A* (pronounced "A-star") search algorithm to objectively select locations that are, on average, the closest to the largest number of the accidents recorded.

The A* algorithm (Hart, Nilsson & Raphael, 1968) is a derivative of the Dijkstra's algorithm (Dijkstra, 1959), which combines its pathfinding strengths with advantages like the heuristic approach of the best-first search (BFS) algorithm (Korf, 1993). Although Dijkstra's algorithm guarantees to find the shortest path by exploring all possible paths methodically, it is inefficient, as it does not prioritise which nodes to analyse first. On the other hand, BFS prioritises nodes using heuristics to estimate the cost of reaching the goal from any given point but does not always find the shortest path, because it might choose suboptimal paths based on a heuristic solution alone. However, the A* algorithm combines both advantages. It guarantees to find the shortest path and improves computing efficiency with an included heuristic estimate. That makes it highly suitable for dynamic environments such as maritime path searches in geographically complex areas. These advantages of the A* algorithm have already been recognised in previous efforts to solve navigational problems.

In addition, the Dijkstra and A* algorithms have proven to be desirable route selection choices for navigation in ice-covered waters (for example, Arctic shipping). With the ongoing climate change, the Arctic passage connecting Asia and Europe has become more appealing to shipping companies than the common route through the Suez Canal. Powerful tools, such as computer-based path search algorithms, are becoming widely used in planning navigation in waters with high spatial and temporal variability of the available sea passages. The authors have agreed to implement uncertainties in sea-ice behaviour in the algorithm as a safety parameter, in addition to considering obvious factors, such as distance, voyage time, and fuel consumption (Browne et al., 2022; Choi et al., 2015; Lehtola et al., 2019; Mishra et al., 2021; Nam et al., 2013). In maritime science, these factors are frequently used to resolve ship routing challenges (Novac et al., 2020). Finding the shortest route in multimodal transportation (container transport) is a useful tool in transportation system optimisation (Qiu, 2010), as well as in introducing unmanned ships (Wang, 2021).

Considering the existing successful results in similar subfields of maritime navigation, the A* algorithm can be a valid choice for research on the optimal distribution of the surface SAR fleet. In this study, the A* algorithm is used in its novel application for a computer-based search of the shortest route between several potential SAR locations and sites of maritime accidents. The authors present a literature review on this subject in the following chapter.

2. LITERATURE REVIEW

Numerous authors emphasise the imperative of strategic and systematic positioning of Search and Rescue (SAR) units. Azofra et al. (2007) highlight the need for collaboration across local, regional, national, and international levels, advocating for the relocation of units based on current needs within specific areas. They emphasise the need to monitor maritime traffic, adjust strategic zones, and amend the National Search and Rescue Plan. Razi and Karatas (2016) introduced the Incident-Based Boat Allocation Model (IB-BAM), a multi-objective framework designed to optimise the allocation of search and rescue resources. This model aims to minimise incident response times, reduce fleet operating costs, and address discrepancies between a vessel's operational capacity and its overload. In paper focused on the Aegean Sea region, Karatas (2021) proposed a deployment strategy that considers response time, workload, and available financial resources. The model explains the seasonal relocation of vessels and integrates joint demand to cover multiple units.

Multi-objective mathematical models form the cornerstone of the majority of scholarly works on this subject, concentrating on enhancing the acceptability, effectiveness, and efficiency of maritime SAR services. While the criteria in these models vary, they universally strive to resolve the so-called location-allocation problem of SAR units. Akbari et al. (2018a, 2018b) aim to optimise this problem for the Canadian Coast Guard using criteria such as primary and backup coverage, arrival time, service quality, and costs. They categorise facilities based on their capabilities, availability, and the spatial distribution of historical accidents to simulate future demand. Their model considers four types of SAR vessels, prioritising time over distance as the primary criterion. Jin et al. (2021) use three types of SAR vessels for long-range maritime SAR operations in oceanic regions, utilising a multi-objective growth simulation algorithm (MO-PGSA) to determine optimal locations for SAR bases and dynamic duty points.

Guo et al. (2019) made an attempt to maximise the probability of operation completion and the utility of allocated resources for long-range maritime SAR by integrating aeronautical and marine units. Zhou (2019), Sun et al. (2022), and Dong et al. (2024), who consider the characteristics of sea areas and identify accident black spots in their studies, also emphasised the significance of mixed fleet allocations. Pelot et al. (2015) adopted a multi-criteria approach to optimise coverage, response time, workload balance, vessel utilisation, and budgetary constraints. Chen et al. (2023) focused on minimising coverage time for Hong Kong waters, while Hornberger et al. (2022) developed a spatiotemporal maritime accident forecast using historical data to optimise the placement of heterogeneous response units, thereby minimising relocation costs.

Siljander et al. (2015) introduced an innovative approach to GIS-based travel-cost modelling, integrating wave height rasters and vessel speed measurements to develop cost-distance models from which response times are derived, however, with certain limitations. Medić et al. (2019) emphasise the importance of integrating new technologies, such as unmanned aerial vehicles (UAVs), to reduce response times. This approach offers a real-time situation overview and minimises false alarms. The paper further delineates the components of total response time as follows:

- the interval between the accident and its confirmation by the Maritime Rescue Coordination Centre (MRCC),
- the period between establishing the location/identifying the accident and dispatching the initial units to the scene,
- the time required for rescue units to reach the accident location.

According to the above-mentioned research background, several criteria can be applied to Croatian waters. This paper serves as the initial exploration of these criteria. The research will be elaborated in the following chapter.

3. METHODS

Croatia currently has at its disposal 48 vessels of the Ministry of the Sea, Transport, and Infrastructure, 38 vessels of the Ministry of Internal Affairs, and the aerial units of the Ministry of Internal Affairs and the Ministry of Defence. Tugboats, environmental protection units, vessels, and privately owned aircrafts are also engaged where needed (MMPI, 2023).

As the first step of the research, the MRCC maritime accident database was sampled for all accidents, regardless of type, where SAR intervention was performed within the area of service authority over a 5-year period (Jan. 2017 – Oct. 2023). A total of 3,366 accidents were chosen, along with their geographical positions. Consequently, the authors identified 214 potential locations along the Croatian coast and islands suitable for permanent Search and Rescue (SAR) maritime facilities, depending on existing infrastructure.

The next task was to determine the nearest facility for each recorded accident from the extracted database sample. The challenge in finding the shortest route lies in the fact that the surface SAR fleet must navigate through obstacles (coast, islands, shallow water, etc.) to reach the site of the accident. If there are no obstacles and the entire area between the facility and the accident site consists of navigable waters, the simple plane distance equation (for short distances) or haversine equation (for longer distances) can be used to find the facility nearest to each accident site. In the real-world context, this is uncommon, so a different solution is required to address the issue.

In this study, the problem of identifying the shortest route was solved by using the A* search algorithm between two geographical points on a matrix representing both land and water pixels. These two points correspond to the proposed SAR facility location and the position of the accident. The A* search algorithm was applied iteratively in a nested loop over all proposed facilities and recorded accident positions in order to determine the nearest facility for each recorded accident during the period concerned. A combined count of 214 proposed facilities and 3,366 accidents resulted in 720,324 runs of the A* search algorithm.

Croatian waters (land and water) were presented using the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) dataset, which has a spatial resolution of 30 arcseconds in the horizontal direction. This resolution allowed the authors to create a grid with approximately 500x500 m spacing. Using this dataset, the authors extracted a LANDMASK variable, which resulted in a 0|1 matrix. In this grid, zeroes denote navigable areas (water), whereas ones represent non-navigable areas (land). The final grid, covering the entire area of interest in Croatian waters, had the dimensions of 1,000x1,000 pixels. Figure 2 shows the resulting matrix, accompanied by an example of the shortest route solved by the A* algorithm between two arbitrarily selected points.

The A* search algorithm was designed to find the shortest route by avoiding non-navigable areas, such as land, and by utilising only navigable areas, which in this context is water. Essentially, the A* algorithm is a graph traversal and pathfinding algorithm based on the principles of Dijkstra's algorithm, which enhances it with a heuristic component to prioritise the exploration of more promising paths. Lawande et al. (2022) classified it as a deterministic pathfinding algorithm with a heuristic (informed) search function. Such a function provides additional information about nodes that have not been explored yet, in order to decide which of them to explore next. This heuristic-guided approach makes the A* algorithm more efficient, and results in the faster identification of the shortest path by avoiding checking unpromising nodes.

In the A* algorithm, each pixel in the matrix serves as a node (n), where zeroes (representing water) denote traversable nodes, whereas ones (representing land) are obstacles or non-traversable nodes (Figure 1).

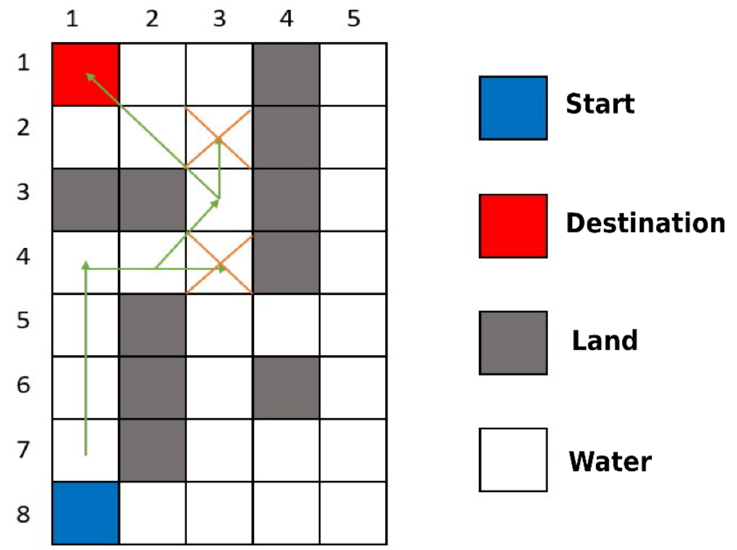

Figure 1. The basic schematics of the A* search algorithm progression from the start toward the destination point within a matrix of navigable (water) and non-navigable (land) pixels. Source: Adapted from Lawande et al. (2022)

The $g(n)$ is defined as the actual cost of the path from the starting node to any node n. $H(n)$ represents the heuristic estimated cost from node n to the destination. For distance calculation, the Euclidean distance formula was applied between two points, denoted as (x_1, y_1) and (x_2, y_2):

$$d = \sqrt{((x_1 - x_2)^2 + (y_1 - y_2)^2)} \tag{1}$$

Finally, the cumulative estimated cost through each node n is calculated as:

$$f(n) = g(n) + h(n) \tag{2}$$

The algorithm operates within a loop and selects the node with the lowest $f(n)$ value at each step. Upon reaching the destination node, the shortest path is identified and reconstructed by back tracing from the goal node using parent pointers.

The basic steps of the A* algorithm are as follows (Hart, Nilsson & Raphael, 1968):

1) At the beginning, the open list has to be defined and the start node selected. The closed list is initialized, too, as an empty one. The g value of the start node is set to 0 and its f value is calculated using heuristics.
2) The loop runs until the open list is empty or the target is reached. The loop runs on selecting the node with the lowest f value from the open list. If the selected node is the target node, the loop is terminated. Otherwise, the node must be moved to the closed list, and the loop continues running.
3) When the target node is reached, the path is reconstructed by back tracing from the target to the start node using parent pointers. These parent pointers effectively record the paths taken during the search.

In the explained steps, non-traversable nodes (land) are excluded from the search process, ensuring that the algorithm considers only viable paths through navigable waters.

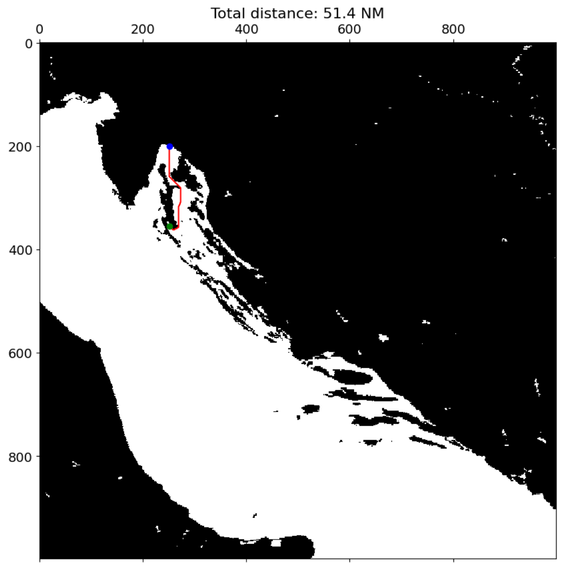

Figure 2. The 1000x1000 pixel search matrix comprises zeroes (white, representing water) and ones (black, representing land).

Figure 2 illustrates the A* algorithm's solution for the shortest route between the starting position (indicated by the blue dot) and the destination (indicated by the green dot), along with the total route distance measured in nautical miles.

By applying the A* algorithm to every combination of proposed SAR facility locations and documented accidents, the facility with the most optimal route to each accident was determined. Following that, the frequency of cases in which a facility was identified as the one with the shortest path to each accident was determined. This procedure made possible the assessment of the appropriateness of each proposed SAR facility site based on the proximity and accessibility of locations with the highest number of accidents.

4. RESULTS

The statistical analysis of the recorded accidents provides insight into the frequency of (SAR) operations along the eastern Adriatic coast (territorial waters of the Republic of Croatia) over the analysed period. Figure 3 illustrates a heat map of the interventions recorded in the area.

Figure 3. Heat map of recorded interventions in 2017-2023. Colour is proportional to the spatial density of interventions. The red colour represents the highest density of interventions.

The results of the A* model, which was fed with data as described in chapter *Methods*, are shown in Table 1, column ‘Count’. The algorithmic decision-making process must be further refined to select specific proposed locations as the best solutions for the SAR facility. This refinement is necessary for managing situations where the A* model assigns similarly high scores to two or more proximate locations. In addition, it facilitates the inclusion of a degree of redundancy for locations significantly affected by the number of interventions.

Only specialised vessels defined as primary maritime rescue units were included in further research (the ones managed by MRCC). Other units with different roles that could be used if needed were not included in the research because their permanent mooring location was defined by different criteria.

The proposed distribution of the SAR fleet for every site was determined based on the proportionality of its number of interventions (counts). The allocation was calculated using the following equation:

$$number = \frac{count}{\sum(counts)} \cdot totalunits \tag{3}$$

In this equation, the term 'count' in the numerator represents the number of interventions calculated by the A* model for a specific location, and the denominator represents the total of the counts across all selected SAR locations, as outlined in Table 1. In this case, one unit was chosen for the results from Equation 3, where decimal value is less than one. Similarly, two units were chosen in cases where the result exceeded two. This approach acknowledges the value of redundancy in high-demand SAR scenarios, although deploying more than two units to a single location can be considered excessive. Nonetheless, this strategy allows for adjustments based on practical field experience. For the results between 1 and 2, the value is rounded to the nearest whole number to determine the allocation of surface SAR units per location. Consequently, the total number of deployed units is 45, with three units remaining in reserve, adding up to 48. These reserve units are available for reallocation where needed, such as during vessel maintenance periods. Although alternative methods for assigning units per location exist, they depend primarily on the size of the reserve unit. The ultimate geographical distribution of these units is illustrated in Table 1 under the “Number of units” column and in Figure 4.

Locations	Count	Number of units
Umag	25	1
Poreč	30	1
Pula	52	1
Rijeka	51	1
Crikvenica	20	1
Stara Baška	29	1
Senj	59	1
Susak	28	1
Rab	47	1
Pag	24	1
Starigrad Paklenica	41	1
Silba	95	2
Molat	125	2
Veli Iž	146	2
Zadar	102	2
Sali	194	2
Piškera (Kornati)	49	1
Biograd na Moru	39	1
Vrgada	72	2
Prvić Šepurine	161	2
Brodarica	122	2
Rogoznica	85	2
Trogir	43	1
Split	43	1
Milna	33	1
Bol	21	1
Hvar	44	1
Komiža	51	1
Ubli	29	1
Vela Luka	25	1
Korčula	29	1
Ploče	30	1
Kozarica	58	1
Koločep	83	2
Cavtat	22	1
Total = 35	Total = 2017	Total = 45

Table 1. The final choice of SAR sites with the most approximate count of recorded incidents and proposed number of surface SAR fleets derived by the algorithm. Locations are sorted out geographically from the northwest toward the southeast.

Figure 4. Geographic map of selected locations for surface SAR fleet distribution, with indicated number of vessels for each selected location

5. DISCUSSION

In previous chapters, a unique solution to the challenge of determining the spatial distribution of surface SAR units was presented. A better distribution will consequently lead to more efficient and successful SAR operations. The methodological approach described herein represents a novel idea that, to the best of the authors' knowledge, has not been used before. Using the A* search algorithm, the statistical distribution of maritime accidents was evaluated to estimate the ideal distribution of surface SAR units, taking into consideration the existing facilities needed for the vessels and the crew.

Although the proposed model was applied to the actual statistical distribution of maritime accidents in Croatian waters, the same approach could be applied anywhere in the world. The results of this model should be used only as an example of how the model could be utilised, rather than as an actual recommendation on how to distribute the surface SAR fleet in Croatian waters. This approach has several limitations that should be addressed in the future use scenario.

Compared to simple mathematical solutions based on explicit distance equations, this approach can solve complex navigational problems, such as searching for the shortest paths between two points and acknowledging non-navigable areas (path obstacles, that is, land). This strong feature makes it especially useful for solving the issue of optimal surface SAR fleet distribution in complex navigation areas with many small islands and rugged coastlines, such as Croatian, Greek, Canadian, and Indonesian waters.

Apart from the example where the model is based on statistics including all months, a more detailed approach can be adopted, too. For example, the seasonal optimisation of surface SAR fleet distribution can also be calculated when using specific seasonal statistics for maritime accidents.

The limitations of the model pertain to the statistical data which lack sufficiently detailed information on maritime accidents. This problem is multifaceted; for example, Strabić et al. (2023) emphasise the importance of detailed information in identifying the root cause of accidents, and their prevention. They proposed the optimisation of the existing data collection and processing system. The existence of several private companies that offer assistance in Croatian waters reduces the completeness and accuracy of the statistical dataset obtained from governmental MRCC. If this approach was an actual recommendation for surface SAR fleet distribution, this statistical deficiency would need to be addressed before feeding the algorithm with the data.

Data on meteorological conditions, sea depth, and SAR vessel drafts were not covered in the model. The locations' infrastructure (accommodation, food, and fuel) and the speed of each type of maritime unit (the average value taken) were not included either. When determining the routes, the grid resolution the algorithm utilises is not sufficient to represent narrow sea passages (straits), which often results in the selection of a longer route. There are several datasets with finer land and sea grids (ex. SRTM, ASTER, etc.) which should be used for a more realistic application of this model.

Furthermore, this paper does not address any benchmarking of the proposed solution. Therefore, it is currently unknown how it compares to solutions proposed by other authors. However, the lack of previous research to solve the optimal spatial distribution in Croatian waters makes the direct comparison to the existing theoretical solutions complex. Therefore, the authors emphasise the ultimate need for further evaluation and research on this subject before the solution can be recommended to the decision-making authorities.

If proven useful, by future research, the existing surface units could be analysed based on their characteristics and aerial and surveillance units could be taken into consideration in order to create an optimal network of all available SAR units within the system. Such a goal could represent a complete solution to the optimal SAR distribution in Croatian waters.

6. CONCLUSION

The stunning natural beauty and diversity of the Croatian coastline have significantly bolstered the tourism industry, particularly the nautical sector. The steady growth in charter operations, combined with the influx of foreign yachts and boats into Croatian territorial waters, has led to a slight increase in the number of maritime accidents. This trend emphasises the need for enhanced SAR service optimisation. Therefore, ensuring maritime safety and the optimal distribution of SAR units present significant challenges.

In this study, an attempt was made to address this challenge by creating a model that could be used for the deployment of surface SAR units. The model utilised statistical data for the period from January 2017 to October 2023. The final result was a selection of 35 locations along the Croatian coastline and archipelagos.

Although limited by certain factors, this model can be applied to other coastal/archipelagic waters, including complex navigation areas. The model could be further improved by including additional parameters and constraints, as well as other types of units to create a more complex and optimised network of SAR units in every area.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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