



Identifying plastic pollution hotspots of Vembanad lake, Kerala, India: an integrated approach using artificial intelligence and spatial analysis

P. P. Ayana · M. R. Sethu · Antony Nirmal ·
M. K. Swetha · V. P. Limna Mol

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Abstract Marine plastic pollution poses a significant threat to marine ecosystems worldwide. This study presents novel approach to identify plastic hotspots integrating artificial intelligence (AI) and spatial analysis. We employed You Only Look Once (YOLO) object detection algorithms to identify plastic debris in field photographs and drone imagery, followed by advanced spatial analysis using ArcGIS Pro to map and analyse the distribution of plastics from 59 sites in the Central Vembanad Lake. The analysis revealed 17 major hotspots, accounting for 270 individual plastic debris. Significant accumulations were observed in Kumbalam (139), Edakochi (135), Chellanam (136) and Kannamali (130). The results demonstrated the potential of integrating AI and spatial tools with UAV imagery for the identification of plastic pollutants and the validation of a scalable monitoring framework for Coastal Ecosystem Management

P. P. Ayana and M. R. Sethu have equally contributed to this manuscript.

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P. P. Ayana · M. R. Sethu · A. Nirmal · M. K. Swetha ·
V. P. L. Mol (✉)
Marine Biology Laboratory, Department of Marine
Biosciences, Faculty of Ocean Science and Technology,
Kerala University of Fisheries and Ocean Studies,
Madavana, Panangad, Kochi, India
e-mail: limnamol.vp@kufos.ac.in

(CEM)."This integrated methodology offers a powerful tool for researchers and policymakers to target cleanup efforts and develop strategies for reducing marine plastic pollution.

Keywords Macroplastics · Artificial intelligence · Spatial tools · Plastic pollution · Hotspot

Introduction

Marine plastic pollution has emerged as one of the most pressing environmental challenges of the twenty-first century, with far-reaching consequences for marine ecosystems, wildlife, and human health (Jambeck et al. 2015). Macroplastic pollution poses physiological issues to marine invertebrates and fish (Browne et al. 2013). Ingestion of microplastics by benthic fauna and zooplankton can lead to contamination of the entire food chain (Green 2016). A recent study by scientists from the Kerala University of Fisheries and Ocean Studies revealed the presence of large quantities of macroplastic litter in the Vembanad Lake system. Inadequate solid waste disposal facilities in the region may contribute to excessive plastic debris entering the lake (Free et al. 2014). The Vembanad lake receives approximately 21,900 Mm³ of water annually through riverine discharge, posing a considerable risk of plastic waste transportation (Thasneem et al. 2018). The lake faces increasing threats from plastic pollution due to urbanization and

inadequate waste management practices (Jeong et al. 2020). Adequate mapping and identification of plastic debris congregations have not been conducted in Vembanad Lake. Microplastics (MPs) persist as ubiquitous pollutants found throughout environments and living organisms (Perumal and Muthuramalingam 2022). The highly durable nature of plastic enables it to remain in environments for extended periods (Lechthaler et al. 2020).

Ocean plastic pollution has emerged as a critical issue across all ocean basins, regardless of regional development status. Ocean plastics are classified into four size categories: mega-, macro-, meso-, and microplastics. Microplastics either come from manufactured consumer products like cosmetics, or form when larger plastics degrade and fragment through physical, chemical, and biological processes (Thushari and Senevirathna 2020).

If current plastic production and waste management practices continue unchanged, estimates suggest plastic waste in landfills and natural environments will reach approximately 12 billion tons by 2050. Oceans function as the main collection point for various pollutants, receiving input through multiple pathways including runoff, rivers, and direct discharge (Ali et al. 2025).

Macroplastics represent a primary source of marine plastic pollution and secondary microplastics, directly impacting ecosystem health and human livelihoods (van Emmerik 2021). Modern drone technology enables plastic waste monitoring in challenging or hazardous areas like river mouths and mangrove forests. Automated monitoring combines multispectral cameras with artificial intelligence. Remote sensing can now detect plastic debris even in Earth's most isolated regions (van Emmerik 2021).

Scientists have extensively documented MP's presence and distribution in seawater, marine sediments, and organisms worldwide (Hale et al. 2020). Due to their persistence, MPs endure in marine ecosystems, distributing throughout the water column based on polymer-specific buoyancy. Their small size makes them susceptible to ingestion and accumulation by diverse marine organisms across taxonomic groups, trophic levels, and feeding strategies. Bioaccumulation of MPs occurs when organisms absorb them faster than they can excrete them, whether through contact, ingestion, or respiration, from water, sediment, or prey sources (Parolini et al. 2023).

Recent advancements in artificial intelligence (AI) and spatial analysis techniques offer new opportunities for detecting and mapping marine plastic pollution. Object detection algorithms, such as "You Only Look Once" (YOLO), have shown promise in identifying plastic debris in environmental imagery (Gavrouzou et al. 2021). When combined with spatial analysis tools, these AI-driven approaches can provide a more comprehensive understanding of plastic distribution patterns. By leveraging cutting-edge technology, we seek to provide a more accurate and efficient means of assessing the extent and distribution of plastic pollution in this vital aquatic ecosystem. The findings of this study have implications for targeted cleanup efforts, policy development, and long-term conservation strategies for the Vembanad Lake and similar water bodies worldwide. This study aims to develop and validate a methodology for identifying marine plastic pollution hotspots in the Central Vembanad Lake (CVL) using a combination of AI-driven image analysis and spatial mapping techniques.

Materials and methodology

Data collection

Building on preliminary survey observations conducted in 2021, comprehensive field sampling was carried out during January–March 2023. The study area encompassed the CVL system, extending from North Cochin Barmouth (Wellington Island) to South Thanneermukkom Barrage, covering a lake surface area of 160.239 km² (Fig. 1). 59 sampling sites were selected using a stratified random sampling approach based on the 2021 preliminary survey, ensuring representative coverage of the CVL system while minimizing selection bias.

Image acquisition was conducted using a DJI Mini 2 drone equipped with its default RGB camera (DJI FC7303, 4:3 ratio). Drone imagery was collected using automated flight paths with 85% side overlap and 85% front overlap at 56 m terrain-following flight altitude, flight operations were conducted using autonomous flight plans programmed via the Map Pilot Pro application, ensuring consistent coverage and minimal human interference. These automated missions maintained terrain following for accuracy and uniform data acquisition across sampling sites,

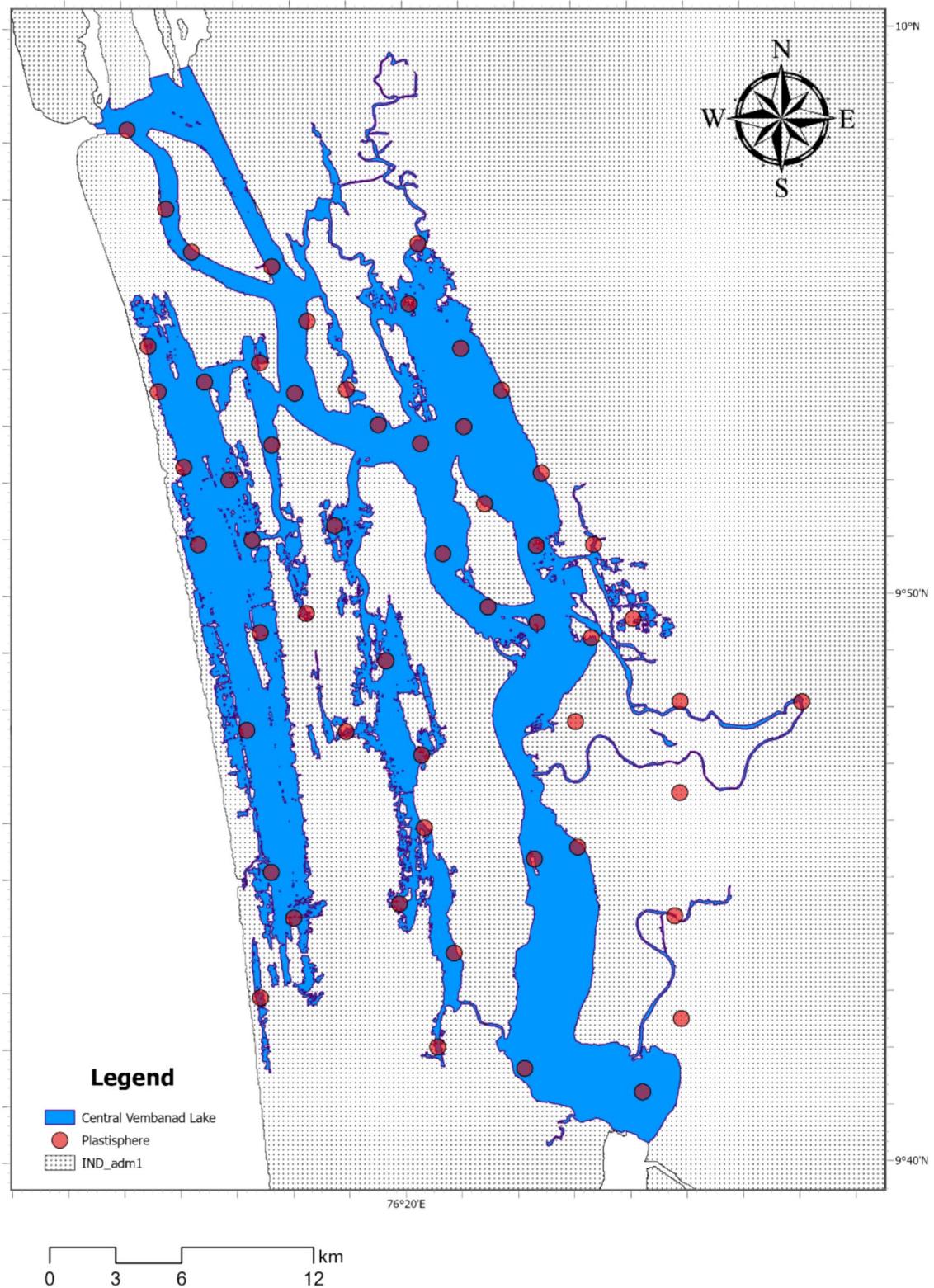


Fig. 1 Study area and sampling sites of the CVL

achieving a spatial resolution of 1.5 cm/pixel (Fig. 2). Field sampling was strategically conducted between 7 and 9 AM to minimize sun glint effects that could

interfere with pixel processing accuracy, though there are algorithms to minimise sun glint effects during data collection (Qin et al. 2024). Each flight covered

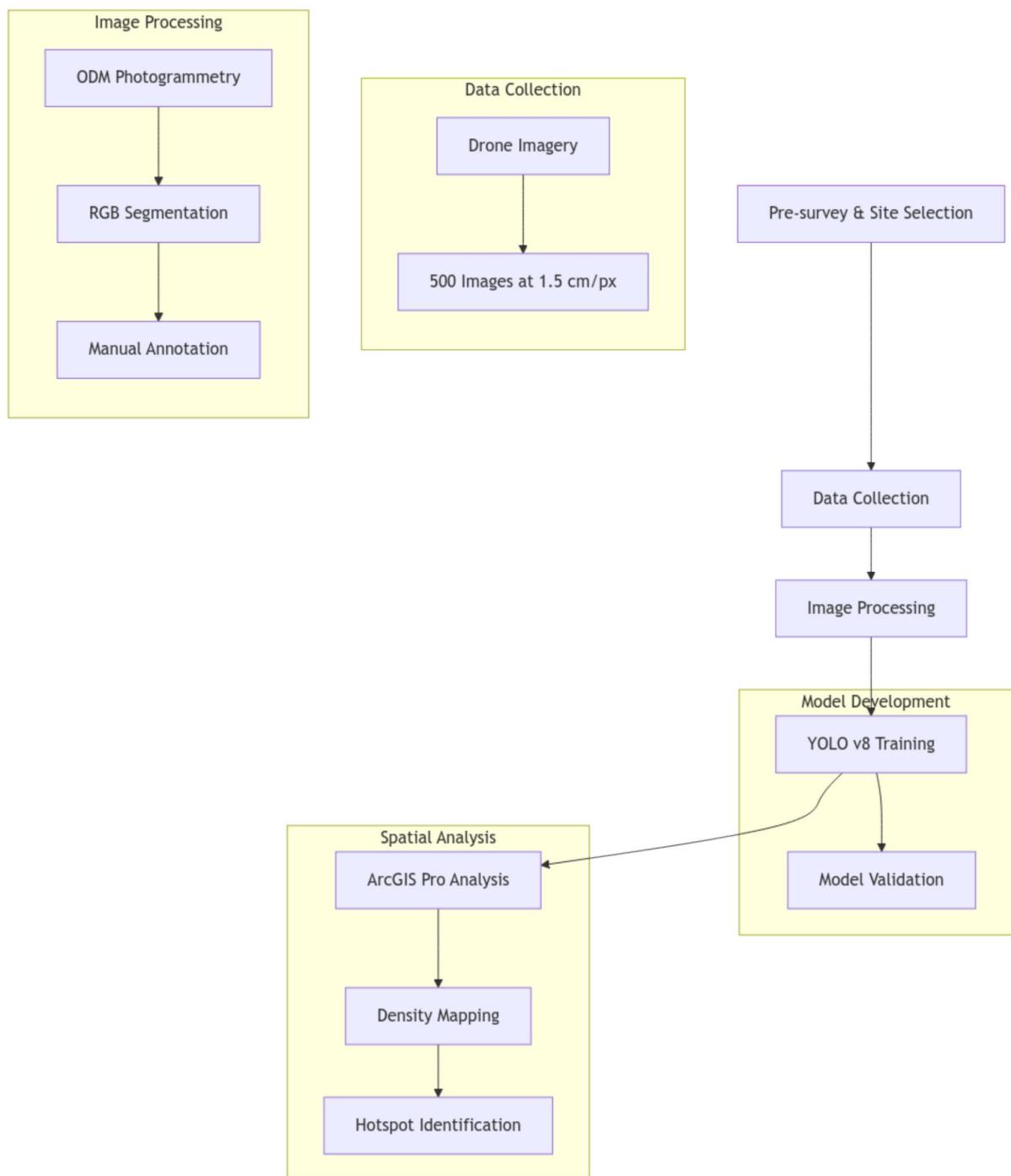


Fig. 2 Methodology flowchart

a pre-defined area, with flight parameters optimized for consistent image quality and comprehensive spatial coverage (Chen et al. 2023; Bhattacharai and Lucieer 2024).

For model training purposes, close-range photographs of debris were captured using the same DJI FC7303 camera to maintain consistency in image characteristics. Photogrammetric processing was performed using open drone map (ODM) to ensure optimal quality of the spatial data (Drone Mapping Software, n.d.). Due to the presence of restricted zones within the study area, drone operations required prior authorization, which influenced the random sampling effort.

The sampling design maintained scientific rigor through:

1. Systematic coverage of diverse environmental conditions
2. Random site selection within accessible zones
3. Representative sampling across different lake segments
4. Strategic positioning to capture varying anthropogenic influences

A total of 500 high-resolution images were captured across the sampling sites, with each image geotagged to ensure accurate spatial referencing (Zhu and Xu 2017). This sampling approach provided comprehensive coverage of key areas while acknowledging logistical constraints inherent in drone-based environmental monitoring of complex aquatic systems (Chabot and Marteinson 2024; Toyomoto et al. 2025).

Artificial intelligence-based plastic detection

The YOLO v8 object detection algorithm was employed to identify plastic debris in the collected images, selected for its high accuracy and real-time processing capabilities in object detection tasks (Somantri et al. 2023). The model was pre-trained on the COCO dataset and fine-tuned using a carefully curated training dataset comprising 1000 manually annotated images (Fig. 3). To minimize training bias and ensure robust model performance, the training dataset was strategically constructed to include:

1. Diverse debris types:

- Various plastic items (bottles, bags, packaging)
- Different sizes and shapes of debris
- Multiple degradation states
- Items under varying lighting conditions

2. Environmental variability:

- Different water surface conditions
- Various background types (vegetation, water, shoreline)
- Multiple viewing angles and distances
- Different times of day and lighting conditions

To address potential false positives, particularly from macrophytes and natural debris, we implemented a two-step validation process:

- I. Manual review of detected objects
- II. RGB image segmentation for enhanced classification accuracy

The model achieved an average precision of 92% across varied environmental conditions, with systematic validation performed to ensure consistent performance across different debris types and environmental scenarios. To further assess model performance, we calculated additional metrics, including recall and F1-score. The YOLOv8 model demonstrated an average recall of 87% and an F1-score of 89%, indicating reliable detection capability in diverse aquatic environments. False positives, primarily associated with macrophytes and driftwood, were mitigated through a two-step validation workflow combining manual review and RGB segmentation refinement (Somantri et al. 2023; Khriss et al. 2024). This approach of transfer learning, combined with comprehensive training data curation, has proven effective in similar environmental monitoring applications (Khriss et al. 2024).

Spatial analysis

Spatial analysis was performed in ArcGIS Pro Intelligence (Esri, Redlands, CA), leveraging the high-resolution imagery (1.5 cm/pixel) obtained through optimized drone flight parameters. This fine-scale resolution enabled detailed mapping of macroplastic debris while acknowledging the challenges of detection in areas with complex vegetation (floating



Fig. 3 Plastic pollutants observed from the photographs using yolo algorithms from in situ photographs (UAV RGB images, and Camera Images)

macrophytes, wet marshes, and aquatic grasses). The analysis workflow included:

1. Creation of a point feature class representing detected plastic items, with each point attributed with debris type and count. The high spatial resolution allowed precise positioning of debris items, particularly important in areas with dense vegetation cover.
2. Generation of point density and kernel density rasters to visualize the spatial distribution of plastic pollution. We employed a multi-scale approach:
 - Initial analysis using a 500 m search radius and 100 m cell size for broad pattern identification

• Refined analysis utilizing the full 1.5 cm/pixel resolution for detailed hotspot examination

• Optimization of density parameters based on local environmental conditions

3. Hot Spot Analysis (Getis-Ord Gi) to identify statistically significant clusters of high and low values, incorporating the enhanced spatial resolution data. This method has been effectively used in previous studies to identify pollution hotspots (Simanungkalit et al. 2024).

While the 1.5 cm/pixel resolution significantly improved debris detection capability, limitations exist in identifying microplastics due to:

- Complex vegetation patterns in the study area
- Technical constraints of RGB imaging in distinguishing small plastics from organic matter
- The need for specific spectral bands and advanced training datasets for reliable microplastic detection

The integration of these methods, coupled with high-resolution imagery, enabled comprehensive analysis of macroplastic pollution distribution and identification of hotspots within the CVL. Future studies could build upon this foundation by incorporating hyperspectral imaging and expanded training datasets for microplastic detection.

Result

Our study encompassed 59 sampling sites across the CVL. The YOLO v8 model achieved an average precision of 92% in identifying plastic debris across our dataset, with false positives primarily associated with natural debris such as driftwood and macrophytes by RGB image segmentation (Fig. 3) (Water Hyacinth, Alligator weed).

Spatial analysis revealed significant variations in plastic debris density throughout the study area. Out of the 59 sites, 17 stations were identified as major hotspots, collectively accounting for 270 individual plastic debris items. Kernel density estimation highlighted areas of high plastic concentration, with peak densities observed in several key locations, particularly in Kumbalam (139 per m²) (Fig. 4).

Hot Spot Analysis (Getis-Ord Gi) identified several statistically significant hotspots of plastic accumulation within the CVL. The primary hotspots were Kumbalam (139) Edakochi (135), Chellanam (136) and Kannamali (130) (Fig. 5). Plastic concentration ranged from 71 to 139 per m². Among the study sites, three locations showed particularly low concentrations of plastic debris: Vaikom (69 items), Thannermukkam (75 items), and Thavanakadavu (94 items).

These findings indicate a non-uniform distribution of plastic pollution across the CVL, with certain areas acting as significant accumulation points for debris. The spatial pattern of hotspots suggests a potential correlation with urban centres and known waste discharge points (Fig. 5).

Discussion

Our integrated approach of AI-driven detection and spatial analysis has revealed clear patterns in the distribution of marine plastic pollution within the Central Vembanad Lake. The identification of 17 major hotspots among the 59 sampling sites underscores the heterogeneous nature of plastic accumulation in this ecosystem, aligning with findings from similar studies in other aquatic environments (Zhang et al. 2022).

The emergence of Kumbalam as a primary hotspot, along with significant debris counts in Edakochi, Chellanam and Kannamali suggests that these areas may be particularly vulnerable to plastic accumulation. Several factors could contribute to this pattern:

1. Local hydrodynamics: The flow patterns within the lake may concentrate debris in these areas, similar to the accumulation patterns observed in coastal marine environments (Lebreton et al. 2018).
2. Proximity to pollution sources: These hotspots are located near points of plastic entry into the lake system, such as urban areas or river mouths, as observed in other studies of freshwater plastic pollution (Blettler et al. 2018). Kannamaly, located near cochin bar mouth, increasing tourist activity has contributed to anthropogenic pressures, including waste generation from individuals and households. Kumbalam, human activities, particularly household waste dumping, along with the presence of the railway, have significantly impacted the area. Chellanam, a centre for boats and a fishing harbour, also faces substantial anthropogenic pressures due to the fishing industry and associated activities, which add to the growing environmental concerns in the regions.
3. Shoreline morphology: The shape and characteristics of the shoreline in these areas may trap and accumulate floating debris more effectively than other locations, a phenomenon also noted in coastal plastic accumulation studies (Critchell and Lambrechts 2016). In addition to anthropogenic factors, physical processes such as tidal exchange, sedimentation dynamics, and lake-wide water circulation may significantly influence the spatial redistribution of plastic debris. Vembanad Lake, being a brackish water body connected to the Arabian Sea through the Cochin

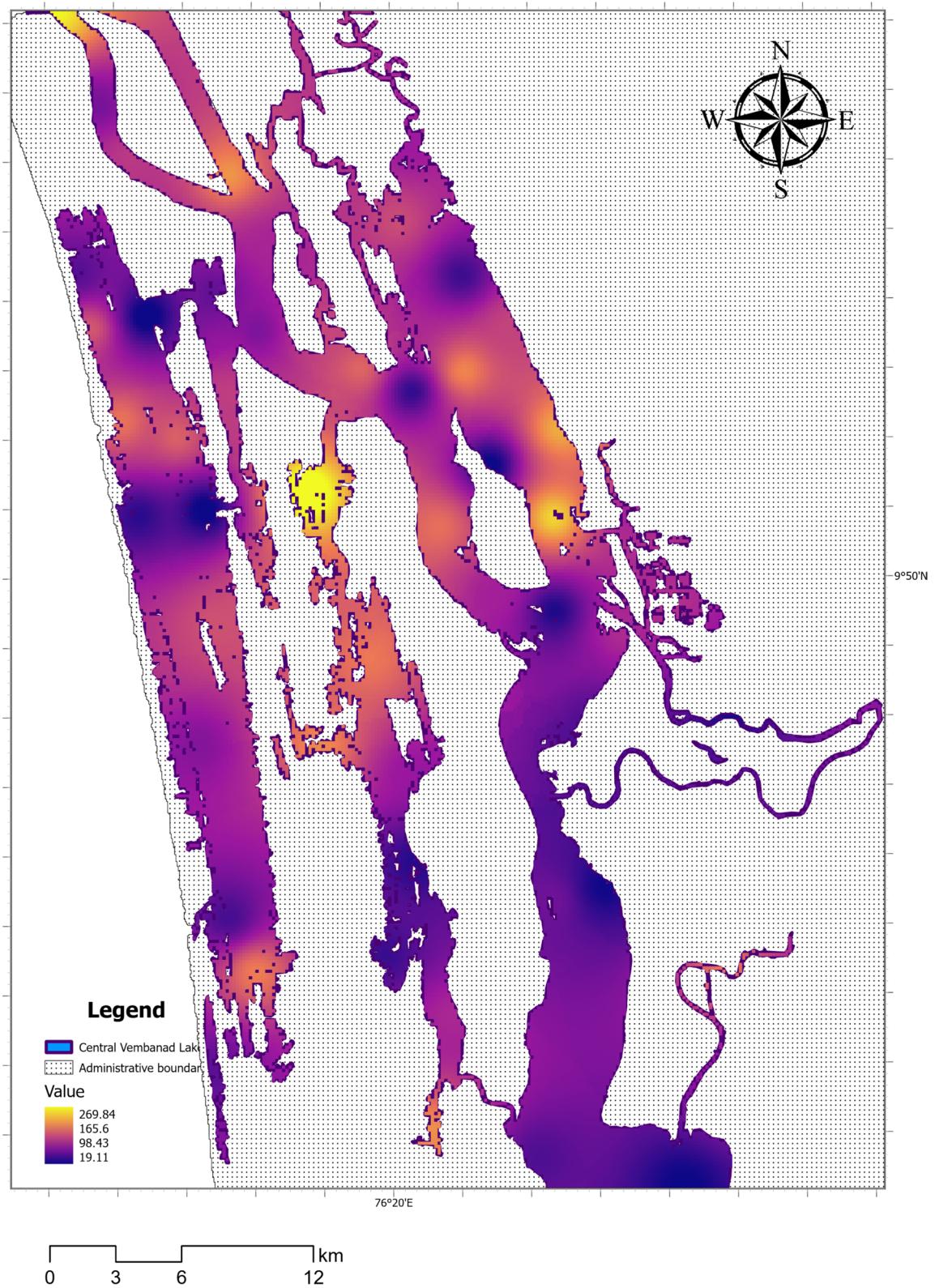


Fig. 4 The map indicates the Dense polluted coastal and wetland system (Yellow color indicates higher density of plastic pollutions)

bar mouth, experiences semi-diurnal tidal fluctuations that can result in the back-and-forth movement of floating debris. These tidal currents, coupled with surface wind patterns and inflow from multiple rivers, can promote the aggregation or dispersal of macroplastics. Additionally, sedimentation processes, especially in zones of low turbulence or high organic load, may trap or bury plastics, influencing their detectability via aerial platforms. While these dynamics were not quantitatively analyzed in the present study, their potential influence is acknowledged and should be investigated in future modelling-based assessments (Critchell and Lambrechts 2016).

Identification of Edakochi, Chellanam, Kannamali and Kumbalam as significant hotspots aligns with their proximity to urban centres and known waste discharge points. This pattern suggests that urban runoff and direct dumping may be major contributors to plastic pollution in the CVL, a finding consistent with studies in other urban-adjacent water bodies (Kataoka et al. 2019) (Fig. 4). To address this observation, future research shall employ multivariate statistical analysis to quantify the relative contributions of urban runoff, fishing activities, and shoreline morphology to plastic accumulation patterns.

While we identify these areas as significant hotspots, we acknowledge that multiple overlapping anthropogenic factors (tourism, fisheries, urban waste) likely contribute simultaneously to plastic accumulation. This complexity presents challenges in isolating individual pollution sources and highlights the need for integrated management approaches addressing multiple human activities within these zones. A summary of anthropogenic factors contributing to plastic accumulation at each hotspot (e.g., urban waste, fishing activity, tourism) is provided in Table 1. This categorization facilitates localized intervention planning and enhances the interpretive value of spatial analysis outputs (Landrigan et al. 2020; Anitha et al. 2024). There are several ways that plastic garbage reaches lakes, and these are mostly caused by human activity and natural processes. Plastic bottles, bags, and food wrappers are among the trash items that urban runoff and precipitation bring into lakes from sidewalks and roadways. Additionally contributing to plastic pollution are industrial discharges from factories situated close to bodies of

water, especially in cases where waste management procedures are deficient (Landrigan et al. 2020). Plastics from packaging, agricultural goods, and farming equipment are introduced into lakes via agricultural runoff. Plastic garbage ends up in or close to lakes as a result of waste mismanagement, particularly in places with inadequate recycling and disposal facilities (Dusaucy et al. 2021).

While our study focused on macroplastic detection using RGB sensors optimized for spatial resolution, future applications could extend this methodology to microplastic monitoring through the integration of hyperspectral imaging and AI-based spectral analysis. Such advancements would require specialized sensors beyond RGB capabilities and more sophisticated training algorithms to detect smaller plastic particles amid complex environmental backgrounds. The YOLOv8 algorithm was selected over other object detection models due to its superior balance between detection accuracy and real-time processing efficiency, which is critical for UAV-based environmental monitoring. While models like faster regions with convolutional neural networks (R-CNN) and Mask R-CNN offer high precision, they are computationally intensive and less suitable for embedded or field-deployable workflows. YOLOv8's architecture allows effective pixel-based plastic debris detection across diverse environmental backgrounds, making it particularly suitable for drone-acquired RGB imagery in dynamic wetland settings (Somantri et al. 2023; Khriss et al. 2024). Nevertheless, future comparative evaluations using receiver operating characteristic (ROC) or precision-recall (PR) curves between YOLO and alternative architectures are recommended to validate performance across varied aquatic ecosystems (Nagamani et al. 2023).

Although this study was conducted a single season (January–March 2023), the selected time frame offers critical insights into macroplastic accumulation following monsoonal runoff. The CVL receives substantial freshwater discharge from multiple rivers, including the Periyar, Muvattupuzha, and Meenachil, which act as conduits for plastic waste during monsoon periods. As a result, debris that accumulates during the wet season often settles and becomes detectable in the subsequent dry season. Therefore, the dry-season data presented here may reflect cumulative plastic deposition influenced by seasonal hydrodynamics (Blettler et al. 2018; Dusaucy et al. 2021). Moreover,

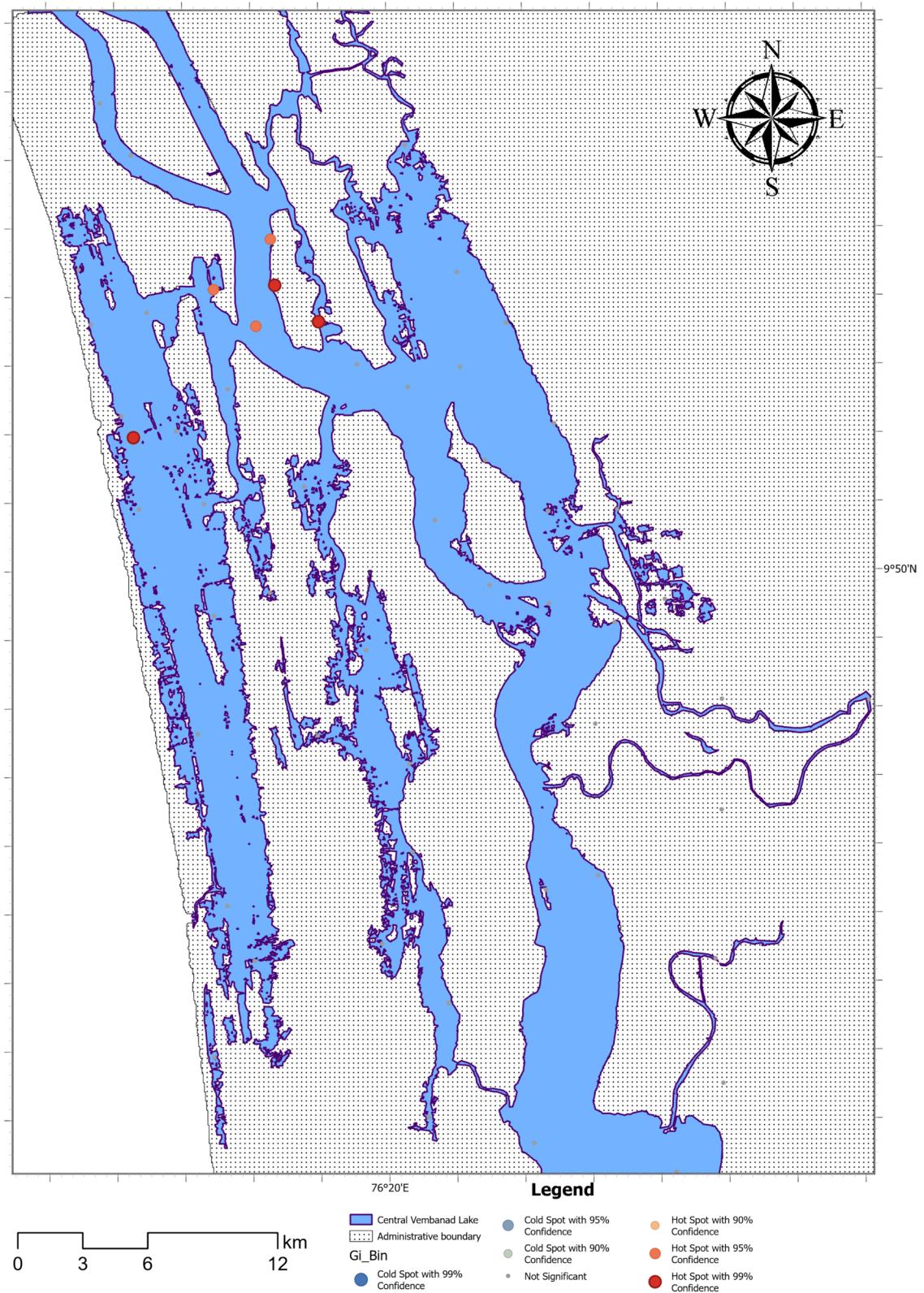


Fig. 5 The map indicates the hotspot identified using Getis-Ord Gi*

Table 1 Dominant anthropogenic sources associated with plastic pollution hotspots in CVL

Hotspot location	Dominant source	Remarks
Kumbalam	Household waste and railway runoff	Near urban settlements
Chellanam	Fishing harbor debris	High boat density
Edakochi	Urban stormwater	Residential dumping
Kannamali	Tourism and coastal activity	Nearby beach visitors

executing UAV-based seasonal surveys over large spatial extents with high-resolution object detection models requires significant data processing capabilities and advanced sensors such as multispectral or hyperspectral platforms, which were beyond the scope of this study (Thasneem et al. 2018; Kataoka et al. 2019). Future research should prioritize temporal expansion and higher-specification platforms to capture seasonal variation more comprehensively.

Recommendation

The identification of 17 plastic pollution hotspots in Central Vembanad Lake through AI-based detection and spatial analysis provides crucial insights for developing targeted intervention strategies. Based on our findings, we recommend implementing an integrated approach combining smart waste management systems near identified hotspots (Anagha et al. 2023) with community-based monitoring using mobile applications for real-time pollution reporting. This should be supported by strengthened regulatory frameworks, including graduated penalty systems for illegal dumping (Uhri and Nemes 2024) and economic instruments such as deposit-refund systems for plastic containers (Martinho et al. 2024). The effectiveness of these interventions can be enhanced through regular monitoring using drone technology and AI-based detection systems (Anitha et al. 2024), coupled with targeted education programs and citizen science initiatives that foster community engagement in pollution monitoring (Sinha et al. 2024). This comprehensive approach, implemented through a coordinated effort between government agencies, local communities, and research institutions, can significantly reduce plastic pollution in Central Vembanad Lake, while serving as a model for similar aquatic ecosystems.

Summary

This study demonstrates the potential of integrating AI and spatial analysis techniques to efficiently identify and map marine plastic pollution hotspots in complex aquatic ecosystems like the Central Vembanad Lake. The methodology developed here can be applied to large scaled geographical areas and adapted to monitor changes in plastic distribution over time.

The identification of specific hotspots in the Central Vembanad Lake provides valuable information for guiding targeted cleanup efforts and informing policy decisions aimed at reducing plastic input in the most affected areas. Moreover, the spatial patterns revealed by this study offer insights into the dynamics of plastic pollution in the lake, which can inform broader conservation strategies in coastal ecosystem management (CEM).

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Author contributions Ayana P P: Sampling, Analysis, Manuscript preparation Sethu M R: GIS and Image analysis, Extensive revision of the manuscript Antony Nirmal: Data collection Swetha M K: Data processing and Revision of the manuscript V P Limna Mol: Formulation of work plan, manuscript preparation and edition.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

References

- Ali SS, Alsharbaty MHM, Al-Tohamy R, Schagerl M, Al-Zahrani M, Kornaros M, Sun J (2025) Microplastics as persistent and vectors of other threats in the marine environment: toxicological impacts, management and strategical roadmap to end plastic pollution. Environ Chem Ecotoxicol 7:229–251. <https://doi.org/10.1016/j.enceco.2024.12.005>
- Anagha PL, Viji NV, Devika D, Ramasamy EV (2023) Distribution and abundance of microplastics in the water column of Vembanad Lake—a Ramsar site in Kerala, India. Mar Pollut Bull 194:115433. <https://doi.org/10.1016/j.marpolbul.2023.115433>
- Anitha C, Devi S, Nassa VK, Mahaveerakannan R, Baksi KD, Suganthi D (2024) Development of image processing and AI model for drone based environmental monitoring system. J Mach Comput. <https://doi.org/10.53759/7669/jmc202404021>
- Bhattarai D, Lucieer A (2024) Optimising camera and flight settings for ultrafine resolution mapping of artificial night-time lights using an unoccupied aerial system. Drone Syst Appl 12:1–11. <https://doi.org/10.1139/dsa-2023-0086>
- Blettler MC, Abrial E, Khan FR, Sivri N, Espinola LA (2018) Freshwater plastic pollution: recognizing research biases and identifying knowledge gaps. Water Res 143:416–424
- Browne MA, Niven SJ, Galloway TS, Rowland SJ, Thompson RC (2013) Microplastic moves pollutants and additives to worms, reducing functions linked to health and biodiversity. Curr Biol 23(23):2388–2392
- Chabot D, Marteinson SC (2024) Aerial remote sensing of aquatic microplastic pollution: the state of the science and how to move it forward. Microplastics 3(4):4. <https://doi.org/10.3390/microplastics3040042>
- Chen S, Zeng X, Laefer DF, Truong-Hong L, Mangina E (2023) Flight path setting and data quality assessments for unmanned-aerial-vehicle-based photogrammetric bridge deck documentation. Sensors 23(16):7159. <https://doi.org/10.3390/s23167159>
- Critchell K, Lambrechts J (2016) Modelling accumulation of marine plastics in the coastal zone; what are the dominant physical processes? Estuar Coast Shelf Sci 171:111–122
- Drone Mapping Software (n.d.) OpenDroneMap™. <https://static.76.53.21.65.clients.your-server.de/>. Accessed 19 Feb 2025
- Dusaucy J, Gateuille D, Perrette Y, Naffrechoux E (2021) Microplastic pollution of worldwide lakes. Environ Pollut 284:117075
- Free CM, Jensen OP, Mason SA, Eriksen M, Williamson NJ, Boldgiv B (2014) High-levels of microplastic pollution in a large, remote, mountain lake. Mar Pollut Bull 85(1):156–163. <https://doi.org/10.1016/j.marpolbul.2014.06.001>
- Gavrouzou M, Hatzianastassiou N, Gkikas A, Lolis CJ, Mihalopoulos N (2021) A climatological assessment of intense desert dust episodes over the broader Mediterranean basin based on satellite data. Remote Sens 13(15):2895
- Green DS (2016) Effects of microplastics on European flat oysters, *Ostrea edulis* and their associated benthic communities. Environ Pollut 216:95–103. <https://doi.org/10.1016/j.envpol.2016.05.043>
- Hale RC, Seeley ME, La Guardia MJ, Mai L, Zeng EY (2020) A global perspective on microplastics. J Geophys Res. <https://doi.org/10.1029/2018JC014719>
- Jambeck JR, Geyer R, Wilcox C, Siegler TR, Perryman M, Andrade A, Narayan R, Law KL (2015) Plastic waste inputs from land into the ocean. Science 347(6223):768–771. <https://doi.org/10.1126/science.1260352>
- Jeong H, Choi JY, Lim J, Shim WJ, Kim YO, Ra K (2020) Characterization of the contribution of road deposited sediments to the contamination of the close marine environment with trace metals: case of the port city of Busan (South Korea). Mar Pollut Bull 161:111717
- Kataoka T, Nihei Y, Kudou K, Hinata H (2019) Assessment of the sources and inflow processes of microplastics in the river environments of Japan. Environ Pollut 244:958–965
- Khriss A, Elmida AK, Badaoui M, Barkaoui A-E, Zarhloulé Y (2024) Exploring deep learning for underwater plastic debris detection and monitoring. J Ecol Eng 25(7):58–69. <https://doi.org/10.12911/22998993/187970>
- Landrigan PJ, Stegeman JJ, Fleming LE, Allemand D, Anderson DM, Backer LC, Brucker-Davis F, Chevalier N, Corral L, Czerucka D (2020) Human health and ocean pollution. Ann Glob Health 86(1):151
- Lebreton L, Slat B, Ferrari F, Sainte-Rose B, Aitken J, Marthouse R, Hajbane S, Cunsolo S, Schwarz A, Levivier A (2018) Evidence that the Great Pacific garbage patch is rapidly accumulating plastic. Sci Rep 8(1):1–15
- Lechthaler S, Waldschläger K, Stauch G, Schütttrumpf H (2020) The way of macroplastic through the environment. Environments 7(10):73. <https://doi.org/10.3390/environments7100073>
- Martinho G, Alves A, Santos P, Ramos M (2024) Social evaluation of a deposit and refund system pilot project for polyethylene terephthalate packaging. Environ Chall 15:100894. <https://doi.org/10.1016/j.envc.2024.100894>
- Nagamani K, Mishra AK, Meer MS, Anuradha B (2023) Mapping severe tropical cyclone Tauktae across the Arabian Sea and Western Coast of India using remote sensing and machine learning during May 2021. In: 2023 International Conference on Data Science, Agents and Artificial Intelligence (ICDSAAI), pp 1–5. <https://doi.org/10.1109/ICDSAAI59313.2023.10452623>
- Parolini M, Stucchi M, Ambrosini R, Romano A (2023) A global perspective on microplastic bioaccumulation in marine organisms. Ecol Ind 149:110179. <https://doi.org/10.1016/j.ecolind.2023.110179>
- Perumal K, Muthuramalingam S (2022) Microplastics pollution studies in India: a recent review of sources, abundances and research perspectives—a comparison with global research. Reg Stud Mar Sci. <https://doi.org/10.21203/rs.3.rs-535083/v2>
- Qin J, Li M, Zhao J, Li D, Zhang H, Zhong J (2024) Advancing sun glint correction in high-resolution marine UAV RGB imagery for coral reef monitoring. ISPRS J Photogramm Remote Sens 207:298–311. <https://doi.org/10.1016/j.isprsjprs.2023.12.007>

- Simanungkalit MA, Hidayat A, Nugroho RA, Depari AS (2024) Analisis hotspot (Getis Ord Gi*) pola spasial frekuensi kecelakaan lalu lintas di kota balikpapan. *COMPACT* 3(1):1. <https://doi.org/10.35718/compact.v3i1.1156>
- Sinha RK, Kumar R, Phartyal SS, Sharma P (2024) Interventions of citizen science for mitigation and management of plastic pollution: understanding sustainable development goals, policies, and regulations. *Sci Total Environ* 955:176621. <https://doi.org/10.1016/j.scitotenv.2024.176621>
- Somantri, Sujjada A, Bayan YS, Ulum VR, Ilhami FA, Insany GP (2023) Enhanced plastic detection and classification: advancing recognition of plastic varieties using YOLOv8. In: 2023 IEEE 9th International Conference on Computing, Engineering and Design (ICCED), pp 1–6. <https://doi.org/10.1109/ICCED60214.2023.10425093>
- Thasneem TA, Nandan SB, Geetha PN (2018) Water quality status of Cochin estuary, India. Accessed from, <https://nopr.niscpr.res.in/handle/123456789/44425>
- Thushari GGN, Senevirathna JDM (2020) Plastic pollution in the marine environment. *Heliyon* 6(8):e04709. <https://doi.org/10.1016/j.heliyon.2020.e04709>
- Toyomoto Y, Oshima T, Oishi K, Maestre JM, Hatanaka T (2025) Constraint-driven multi-USV coverage path generation for aquatic environmental monitoring (No. arXiv: 2411.00579). <https://doi.org/10.48550/arXiv.2411.00579>
- Uhri L, Nemes O (2024) Examination of environmental legislation (related administrative law and some criminal and civil law) and sanctions for illegal waste dumping in the V4+ countries (Czech Republic, Poland, Hungary, Slovakia and Slovenia). *J Agric Environ Law* 19(36):36. <https://doi.org/10.21029/JAEL.2024.36.225>
- van Emmerik T (2021) Macroplastic research in an era of microplastic. *Microplast Nanoplast* 1(1):4. <https://doi.org/10.1186/s43591-021-00003-1>
- Zhang W, Jiang C, Chen L, Bhagwat G, Thava P, Yang Y (2022) Spatial turnover of core and occasional bacterial taxa in the plastisphere from a plateau river, China. *Sci Total Environ* 838:156179
- Zhu Z, Xu C (2017) Organizing photographs with geospatial and image semantics. *Multimed Syst* 23(1):53–61. <https://doi.org/10.1007/s00530-014-0426-5>

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