Received: 16 February 2024 | Accepted: 30 June 2024 | Published Online: 30 June 2024

Recoletos Multidisciplinary Research Journal Vol. 12 no. 1 (June 2024)

DOI: https://doi.org/10.32871/rmrj2412.01.15

RECOLETOS MULTIDISCIPLINARY RESEARCH JOURNAL

Utilizing IOT and Geospatial Analytics for Sustainable Fisheries Management

Epifelward Niño Amora[1*] and Jovelyn Cuizon[2]

[1]Local Government Unit of Candijay, Bohol, Philippines

[2]School of Computer Studies, Univeristy of San Jose-Recoletos, Cebu City, Philippines

*Correspondence: ninyohamora2017@gmail.com

Abstract

This study developed a software application that integrates Internet of Things (IoT) devices and weather data to visualize prime fishing locations using advanced spatial data techniques. The application features a dashboard that processes and displays real-time data, providing insights into fishing trends, fisherman activities, boat locations, and environmental conditions. The application uses the Graham scan method to generate a GIS grid heatmap for visualizing fish populations and trends, enhancing fisheries management capabilities. Comprehensive testing and refinement ensured the application's usability and adaptability. The results demonstrated high user satisfaction, with a 91% rating in usability and accuracy. The Graham Scan method successfully mapped fishing zones, achieving a 97.96% overlap in spatial-temporal data analysis, proving essential for data-driven decision-making in sustainable fisheries management.

Keywords

IoT, GIS, fishery management, weather conditions, sustainability, mobile application, web application, Graham scan

INTRODUCTION

With its rich maritime landscapes, the Philippine archipelago plays a pivotal role in shaping the local economies and cultural and societal traditions through its historical significance in fishing activities. As the world faces an ever-increasing demand, there's a pressing need to transition from traditional methods to more efficient and sustainable fishing practices.

Many researchers have integrated technology into fishing methodologies amidst technological advancements. Gladju et al. (2022) comprehensively reviewed data mining and machine learning applications in aquaculture and fisheries. Their findings underscore the pivotal role these technologies play in optimizing fish farming and capture fisheries, including improvements in feed use, disease prevention, and catch monitoring. Such innovations promise to boost the efficiency and sustainability of fisheries by facilitating smarter decision-making and more precise operational control. Calderwood (2022) highlighted the expanding reliance on smartphone applications within commercial fisheries, noting their critical role in enhancing various industry aspects—from data collection to regulatory compliance and safety. This study showcases how essential apps have become for efficient operations in commercial wild capture fisheries, improving data gathering and sharing, essential for sustainable management and informed decision-making. Tilley et al. (2020) introduced PeskAAS, an open-source digital platform that uses the Shiny R package and other tools to enhance small-scale fisheries management. By improving data collection, analysis, and visualization, PeskAAS addresses significant data gaps, particularly in dispersed and diverse fisheries, thus supporting more sustainable practices through better-informed decision-making. Additionally, Anuchiracheeva et al. (2003) saw the potential of Geographic Information Systems (GIS) as a tool to harness and streamline local fishermen's knowledge. Complementing this, Agcaoili (2018) demonstrated the efficacy of GIS coupled with a decision support system for spatial identification in resource-focused studies, underscoring the potential of these technologies in the fisheries sector.

Amidst these strides in technological integration, the computational research around Convex Hulls has opened new avenues. Sharif et al. (2012) explored the application of Convex Hulls in virtual reality, particularly for boundary detection in images. Introducing a hybrid method that combines quick hull and Graham's Scan algorithms unveiled potential advancements that could be adapted for more accurate mapping and understanding of fisheries regions and patterns.

However, despite these significant advancements, areas still need to be explored in merging traditional knowledge with contemporary technologies. Dash et al. (2023) provided a bibliometric analysis underscoring ICT's significant impact on fisheries, identifying gaps particularly in socio-economic upliftment and sustainability practices. This finding aligns with recent initiatives in regions like Southeast Asia, where ICT integration has been pivotal but uneven across socio-economic groups. Meanwhile, De Freitas and Tagliani (2009) demonstrated the successful application of GIS to harmonize traditional and scientific data, enhancing artisanal fisheries management in southern Brazil. However, challenges persist in uniformly interpreting this integrated data across different fisheries, highlighting the need for region-specific adaptations. Similarly, Coutinho and Boukerche (2022) advanced the use of IoT with cloud computing and machine learning in smart aquaculture. Their model, promising in controlled environments, still faces hurdles in broader, real-world application due to the complexity of data sources and the need for robust, real-time processing capabilities. These studies collectively reveal a landscape where technology's potential to transform fisheries management is evident. Yet, its full realization requires careful navigation of technological, ecological, and socio-economic variables, particularly in underrepresented regions.

This research endeavors to fill these gaps. Building upon the foundational works of experts like Patil and Sachapara (2017), who championed intelligent IoT solutions, and Bradley et al. (2019), who emphasized the role of innovative technology in fisheries management, our approach uniquely integrates various data sources into a unified, cohesive framework that leverages real-time environmental data alongside traditional fishing knowledge, supported by advanced IoT technologies. Unlike previous methods that may offer static or less adaptable solutions, our system is specifically designed to adjust to various ecological and socio-economic contexts through an innovative configuration of IoT data flows and feedback mechanisms. This dynamic adaptability not only enhances fishing efficiency but also ensures sustainability by facilitating more responsive and precise management strategies tailored to the specific needs of different fishing communities. Our method stands out by its ability to merge real-time data capture with an intuitive user interface, making it accessible for fishers and promoting community-inclusive fisheries management. This approach takes cues from Kolding et al. (2014), Leleu et al. (2012), and Morzaria-Luna et al. (2020), who have underscored the importance of data-driven, community-inclusive, and ecologically balanced approaches to fisheries management.

METHODS

Our research methodology synthesizes classical fishing knowledge, prevalent across diverse marine ecosystems, with the innovation of contemporary digital tools. The System Architectural Diagram (Figure 1) illustrates a streamlined data collection process implemented through a custom-developed mobile application in Android Studio. This application facilitates the real-time recording of catch data by Fish Landing Officers (FLOs), detailing critical parameters such as species identification and weight metrics. Consistent with Musembi et al. (2019), each fisherman or boat is uniquely cataloged to ensure the precision of the collected data.

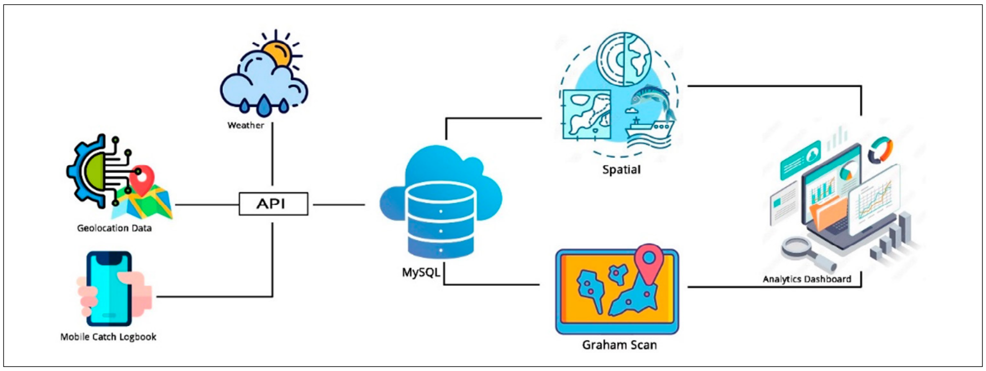


Figure 1. *System Architectural Diagram illustrating the data flow from the data collection to analysis. This diagram was created by the authors specifically for this study*

In parallel, the Internet of Things (IoT) devices are pivotal. Arduino microcontrollers, augmented with GPS and GSM modules and installed on fishing boats, are a nod to the preemptive safety measures advocated by Jeyanathan et al. (2023). These devices are the cornerstone of our data acquisition system, transmitting the collated information through a RESTful API for optimal data flow to a centralized repository, a strategy influenced by the efficient communication protocols outlined by Ong et al. (2015).

The Central Server emerges as the critical repository for all data streams. It processes and retains information from the IoT devices and mobile applications and integrates meteorological data from various weather APIs. Incorporating Google Maps, the server offers a comprehensive view of fishing locations. Notably, it employs the Graham Scan algorithm to create a GIS heatmap, delineating fish distribution patterns, an approach inspired by the research of Lamot and Zalik (2003).

Our system's architecture exhibits inherent scalability, as demonstrated by its seamless operation beyond its initial deployment in Cogtong Bay, Bohol, Philippines. Taking cues from the database management strategies by Wang et al. (2012), the design is capable of managing data from varied fishing operations, establishing its applicability to a range of marine environments.

Validation of the system's capability for broader deployment was achieved through pilot studies and environmental simulations, confirming its proficiency in handling increased data volumes and operational demands, thus endorsing its utility for comprehensive fisheries management.

The culmination of the endeavor is a Web Application, crafted using the CodeIgniter PHP MVC framework, that showcases an analytics dashboard. This platform consolidates fishing data trends and catalog details, enriched with real-time and historical meteorological data, to provide a granular understanding of fishing patterns. This application, resonant with the business intelligence imperatives discussed by Khatuwal and Puri (2022), facilitates swift data dissemination and analytical insight derivation.

Our research promulgates a cyclic approach to data management, underscoring continual collection, transmission, processing, and information display. This model is designed to reinforce fisheries management by integrating the robustness of traditional fisheries research with the agility of cutting-edge technology.

Internet Of Things (IoT) Model

As shown in Figure 2, IoT Architectural Flow expands upon our research methodology, detailing the IoT framework integral to our study. Central to this framework are Arduino Uno microcontrollers equipped with GPS and GSM modules installed on fishing boats, as shown in Figure 3. These microcontrollers are critical for accurately tracking boat routes and fishing spots and are essential in real-time data transmission to our central server. It also illustrates the IoT device setup, including an image of the device installed on a fisherman's boat Figure 3 (A), highlighting its integration into the boat's operations during active data collection phases and a close-up of the IoT prototype pre-installation Figure 3 (B), showcasing components like the Arduino Uno board, GPS and GSM modules, and an LCD for coordinates reading.

The GPS module continuously tracks and records the movement of fishing boats, marking their routes and locations. The accompanying GSM module facilitates the transmission of this data, including latitude, longitude, deviceID, and timestamps, to our central database every three minutes via a RESTful API. The system's design, including a portable 5-volt rechargeable power bank, ensures uninterrupted operation throughout fishing activities.

Our protocol for transmitting geospatial data was rigorously tested in diverse marine environments, including challenging areas with varying signal strengths like dense mangroves and open seas. This testing validated the reliability and effectiveness of our IoT model under different environmental conditions.

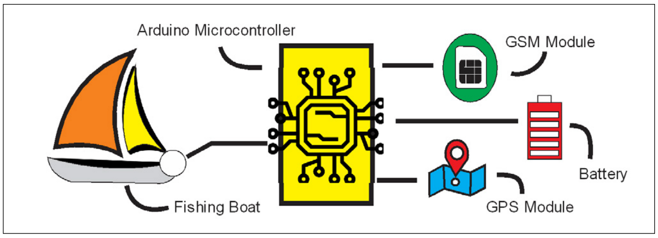
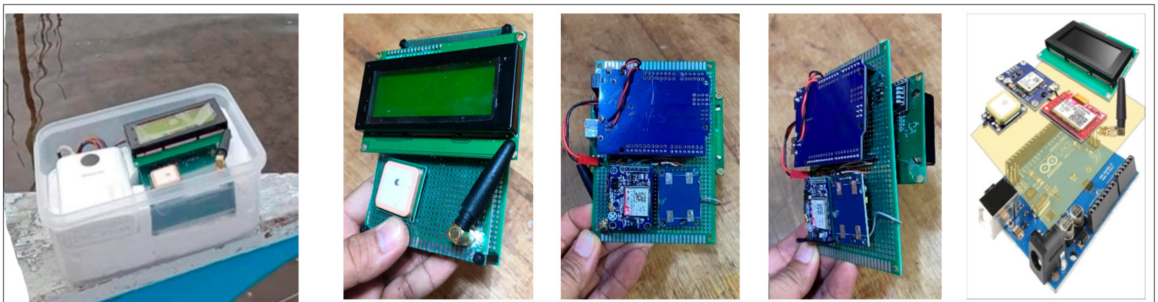


Figure 2. *IoT Architectural Flow*

Data Capture: Fishermen, Species, and Geolocations



(A) IOT device embedded on the boat

Front View *Back View* *Side View* *Isometric Illustration*

(B) Actual IOT prototype

Figure 3. *IoT Device embedded on a Fisherman's Boat in Cogtong Bay*

Utilizing the IoT framework, we capture primary geospatial data from fishing boats in Cogtong Bay, Bohol, Philippines. Each IoT device, assigned a unique fishermanID, gathers and sends critical data to the central database every three minutes, including geolocation points, fishing activities, and environmental data like temperature and wind speed. This multi-faceted dataset offers an extensive view of the region's fishing practices and environmental dynamics, paving the way for informed fisheries management and ecological research.

Following this, Tables 1 and 2 showcase selected examples from the comprehensive datasets collected through our IoT framework. These samples provide detailed insights into the participants and their fishing activities, illustrating the type of data captured and demonstrating the functionality of our system. Please note that these tables show illustrative examples of those that encompass the entire dataset, which includes data from a total of 39 fishermen who participated in the study.

Table 1. *Participants - Lists fishermen with their unique IDs, names, and associated boat numbers*

Fisherman ID	Fisherman Name	Boat Number
FM001	Fisherman 1	2016-C-21340
FM002	Fisherman 2	2016-C-32141
FM003	Fisherman 3	2019-C-18712
FM004	Fisherman 4	2015-C-32123
FM005	Fisherman 5	2016-C-19812
FM006	Fisherman 6	2016-C-18234
FM007	Fisherman 7	2017-C-12343
FM008	Fisherman 8	2018-C-14756
FM009	Fisherman 9	2019-C-15356
FM010	Fisherman 10	2019-C-15432

Table 2. *Fishing Records - Provides a detailed analysis of fishing activities, encompassing data on location, species caught, catch volume, and weather conditions, offering a comprehensive overview of specific fishing events*

Fisherman ID	Latitude	Longitude	Unique Species ID	Catch Volume (kg)	Timestamp	Weather Condition			
						Geolocation Temp (°C)	Atmospheric Pressure	Cloud Cover / Precipitation	Wind Speed (m/s)
FM010	9.6289	124.87	2	90	2019-06-03 05:10:24	26	1010	Scattered Clouds	2.22
FM007	9.8354	124.633	2	10	2019-06-04 06:20:20	27	1010	Overcast Clouds	4.99
FM010	9.87433	124.609	21	18	2019-06-01 05:40:04	28.71	1010	Light Rain	5.67
FM006	9.87347	124.605	21	10	2019-06-06 06:30:12	28.62	1011	Scattered Clouds	4.63
FM006	9.87464	124.61	66	17	2019-06-07 06:06:14	29.49		Few clouds	4.92
FM006	9.87304	124.606	56	3	2019-06-13 05:50:54	29.5	1009	Overcast Clouds	2.97
FM010	9.83694	124.643	56	50	2019-06-19 05:23:54	28.85	1009	Overcast Clouds	1.36
FM006	9.87242	124.615	56	3	2019-06-19 06:15:54	28.85	1008	Overcast Clouds	1.36
FM010	9.83855	124.646	56	59	2019-06-20 05:54:05	28.53	1010	Light Rain	2.62

These tables are instrumental in illustrating the practical application of our IoT framework in capturing and analyzing data, thereby contributing significantly to fisheries research and management.

Gathering Geospatial Data of Fishing Boats and Weather Conditions

Complementing this geospatial data is the real-time meteorological information fetched from the AccuWeather API. This data, synchronized with the boat's location, introduces an environmental context to the dataset. Upon reaching the central server, the data integrates into a web platform and a mobile interface for FLOs. Figure 4: Real-time Location Web Dashboard for Monitoring Fishing Boats aids FLOs in identifying and localizing the fishing boats, ensuring meticulous data logging upon their return.

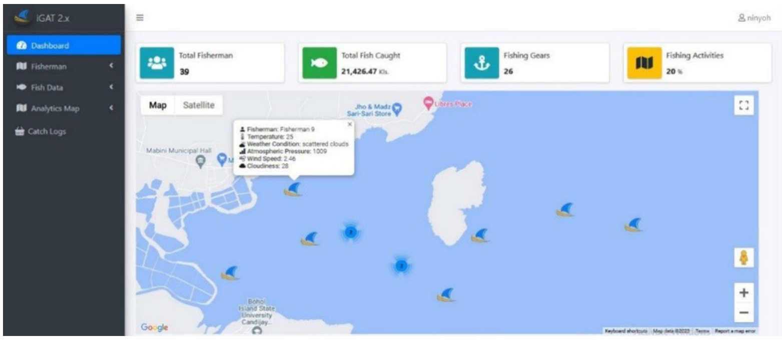
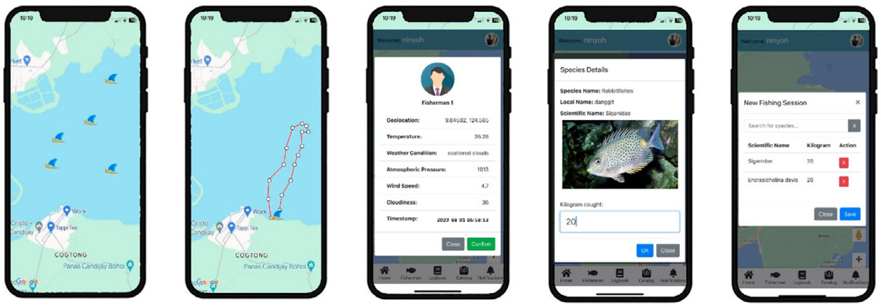


Figure 4. *Real-time Location Web Dashboard for Monitoring Fishing Boats*

Additionally, the mobile application's robust tracking feature, showcased in Figure 5: Historical Tracking Feature on the Mobile Application, enables users to not only backtrace and pinpoint catch locations over specified periods but also to record and register detailed catch data. This integrated functionality allows fishermen and fish landing officers to efficiently log catches, capturing essential information such as species, volume, and precise geolocation. Figure 5 (A) shows the moving fishermen's real-time geolocations, displaying data on a map with icons and showing the fisherman's info when selecting the icon. Figure 5 (B) allows users to view historical routes taken by the boats over time, helping analyze fishing patterns and optimize future routes. Figure 5 (C) confirms the fishing location upon the boat's return, verified by FLOs to ensure accurate catch data. Figure 5 (D) logs the types of species caught and their respective weights, ensuring data integrity at the point of landing. Figure 5 (E) securely transmits catch data to the central server for analysis, with validation steps to ensure accuracy and completeness. Figure 6: Detailed View of Catch Data with Volume, Species, and Location Information offers a holistic perspective on the catch data, underlining critical parameters like volume and species type.



A) Realtime Boat Geolocation

(B) Boat Routes

(C) Fisherman Fishing Location Confirmation

(D) Recording of Species Caught and Weight

(E) Saving Species Caught

Figure 5. *Historical Tracking and Record catch data feature on the Mobile Application*

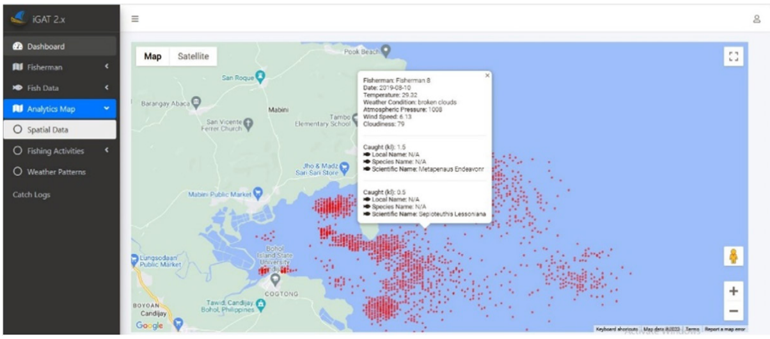


Figure 6. *Detailed View of Catch Data with Volume, Species, and Location*

However, the research encounters specific limitations. The absence of comprehensive boat trajectory data restricts insights into detailed movement patterns of fishing boats. Additionally, the reach of IoT technologies to only a subset of boats in Cogtong Bay might introduce a potential bias in the data collected. A minor concern is the 5% variance in geolocation accuracy compared to commercial devices, which is primarily noticeable in dense mangrove areas. However, this variance is less critical as these areas are typically used for navigation, with the main fishing activities occurring in open areas where data precision is more reliable. Moreover, data from mobile applications and weather APIs might be affected by connectivity issues.

Despite these challenges, the research provides comprehensive insights into fishing patterns by integrating geospatial data with environmental conditions and catch details. This holistic methodology has been crucial in evaluating fishing efforts, clarifying the spatial distribution of marine assets, and assisting in making informed decisions for sustainable fisheries management.

Graham Scan Algorithm Process and its Contextual Significance

The Graham Scan algorithm stands out as an indispensable tool in marine data analysis. The significance of this study's adaptation of the Graham Scan is underscored by the data from 39 fishermen, encompassing 1,574 distinct geolocation points. A salient metric is that each fisherman contributes, on average, to approximately 40.36 geolocation points. To clarify:

- F represents the number of fishermen, marked as 39 in this study.
- G encapsulates the collective geolocation points, summing up to 1,574.
- By computing G/F, the average geolocation points attributed to each fisherman are around 40.36.
- Diving into the procedural mechanics, the Graham Scan algorithm operates predominantly in two stages:

  Phase 1 - Sorting Points: The inception is marked by pinpointing P0, which holds the lowest y-coordinate. For tie-breaking, points with a lower x-coordinate are given priority. After this identification, the ensemble of points is systematically arranged based on their polar angles for P0. Duplicate curves lead to the retention of the distant end. A vital step in sorting is determining whether a convex hull can be formed; if mm (the resultant point count) is under three, the convex hull's formulation becomes untenable.

  Phase 2 - Accept or Reject Points: An unoccupied stack, symbolized as SS, becomes the starting point, populated with the initial trio of sorted points. The orientation of the ensuing points plays a crucial role. A deviation from the counterclockwise direction triggers the extraction of the stack's uppermost point, supplanted by the currently examined point. The culmination sees SS safeguarding the vertices that sketch out the convex hull.

A practical rendition of the Graham Scan algorithm, adapted for this study, is illustrated in the flowchart depicted in Figure 7. This concise diagram provides a function blueprint of the algorithm's operation.

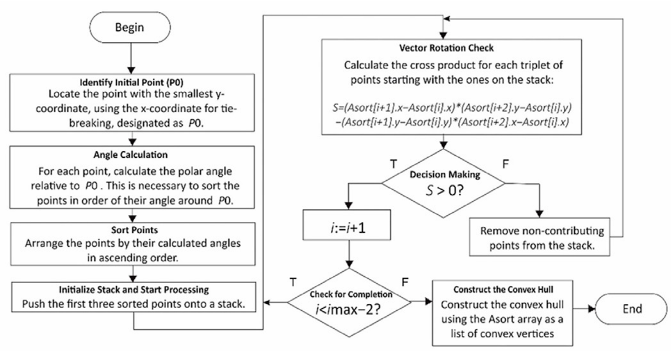


Figure 7. *Flowchart illustrating the Graham Scan algorithm*

Building on the foundational work of Lamot et al. (2003), although their study focuses on simple polygon triangulation, the essence of their work is deeply relevant to our research. Their academic efforts highlighted the computational efficiency of the Graham Scan. In the context of this study, the Graham Scan effectively transforms a vast array of geolocation data into a streamlined convex hull. This transformation accurately delineates each participant's fishing territories, emphasizing the critical boundary markers while minimizing potential internal discrepancies.

From a computational vantage point, the Graham Scan's keystone remains the sorting mechanism, bestowing it with a time complexity of O(N log N). This algorithmic voyage leads to the creation of a convex hull, a clear representation of each fisherman's area of operation, emphasizing the boundary markers. A stepwise schematic of this methodological approach is portrayed in Figure 8, which provides a systematic illustration of this process, highlighting its fundamental stages.

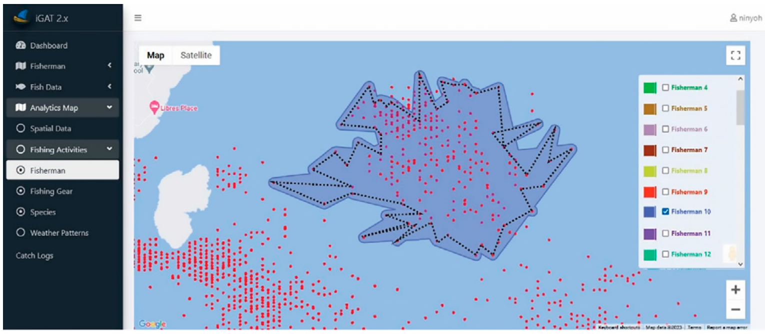


Figure 8. *Visualization of Graham Scan Algorithm for Fisherman 10 - Showing the formation of the convex hull using actual data points (longitude, latitude)*

Fish Catch Integration

To effectively quantify the average volume of catches and the average catch per trip within a given polygon, two distinct mathematical formulas have been formulated.

The first equation represents the average volume of catches (VV_{avg}) for each fish species (NN) within a polygon (PP):

$$VV_{avg} = \frac{\sum_{i=1}^{NN} VV_i}{NN} \text{ (Equation 1)}$$

Where:

- VV_{avg} is the average volume of catches for a fish species.
- VV_i is the volume of catch for the i^{th} fish species.
- NN is the total number of distinct fish species.

The subsequent formula computes the average catch per trip within a designated polygon:

$$Catch_{avg} = \frac{\sum_{j=1}^{PP} Catch_j}{PP} \text{ (Equation 2)}$$

Where:

- $Catch_{avg}$ is the average catch per trip within a polygon.
- $Catch_j$ is the catch for the j^{th} trip within the polygon.
- PP denotes the total number of trips (or polygons).

Polygon Generation and Fish Catch Integration

This section outlines the methodology employed to define the fishing territories of each fisherman using polygons. These polygons are generated from the recorded geolocation points. The chosen instrument for this task is the Graham Scan algorithm, renowned for its efficacy in creating convex hulls.

As shown in Figure 9, individual maps have been curated for each fisherman, highlighting their unique fishing territories through polygonal shapes generated from their geospatial data.

.

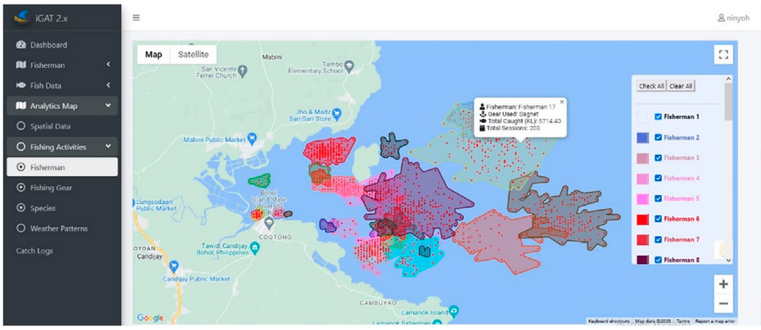


Figure 9. *Individual Fishing Territories illustrated Through Convex Hulls*

Web Analytics Dashboard

The culmination of extensive fishing activities and detailed data capture in Cogtong Bay, Bohol, has been encapsulated into an advanced web analytics dashboard. This dashboard was meticulously designed after the rigorous stages of data collection, processing, and integration, ensuring an interface that mirrors the depth of the research. It serves as a visual bridge, connecting users to the fishing industry's subtle spatial and quantitative dynamics.

In Figure 10, we present the Monthly Caught History Analytics. This graph reveals the patterns of fishing across the calendar, pinpointing fluctuations in catch volumes and their alignment with specific months. It magnifies the evident seasonal variations and the slight details, possibly indicating the influence of underlying ecological or environmental factors.

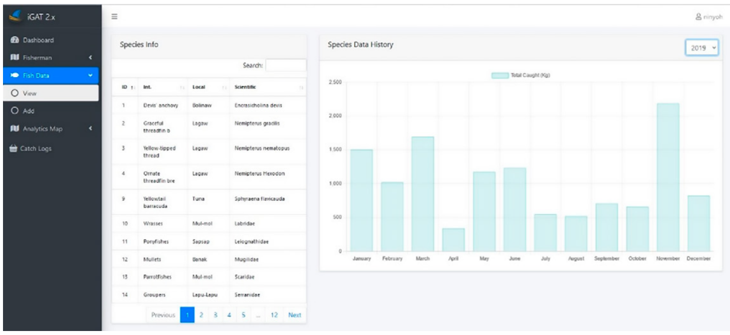


Figure 10. *Monthly Caught History Analytics*

In Figure 11, we delve deeper into the spatial patterns, showcasing Territorial Boundaries by Fishing Gear Type using the Graham Scan Algorithm. This algorithm efficiently converts geospatial coordinates into polygons or convex hulls to outline territories. Each distinct color represents a different fishing gear type, providing insights into fishermen's preferred areas. The map highlights overlapping and common regions, giving stakeholders a clear and data-rich geographic overview. Beyond mere boundary demarcations, this visual representation conveys insights into fishing gear choices, territorial dynamics, and potential environmental influences.

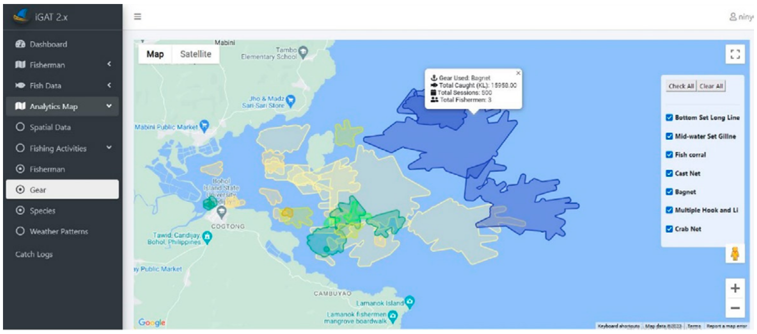


Figure 11. *Territorial Demarcation by Fishing Gear Type via the Graham Scan Algorithm*

Lastly, Figure 12 closely links environmental factors to fishing activities. The interactive heat maps depict the connection between catch volumes and weather conditions. A dynamic date slider illuminates the evolving patterns of fishing activities, allowing users to transition between dates to view real-time fishing trends. Annotations underscore significant weather events, providing context to the visual data.

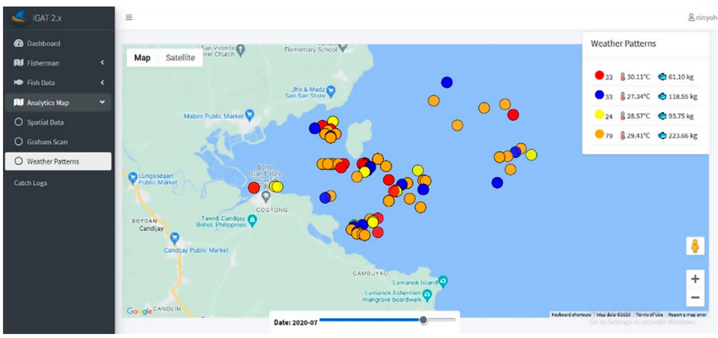


Figure 12. *Interactive Heat Maps showing the Weather Patterns & Fishing Activities*

In addition to the primary data collection methods, our study includes a comparative analysis of various fishing gears employed by the fishermen. Utilizing the data captured regarding gear types, catch volumes, and corresponding environmental conditions (weather, temperature), we aim to assess the effectiveness of each fishing gear. Statistical analyses performed determined correlations between gear types, catch volumes, and environmental factors. The analysis provides better understanding of how different fishing gears perform under varying weather conditions, including insights into optimal gear usage for sustainable fishing practices.

RESULTS AND DISCUSSION

Graham Scan Analysis

Our analysis, as detailed in Table 3, revealed significant insights. Notably, Gear ID 7 was associated with the highest catch volume (15,958 kgs) over an area of 2,081.6 hectares, despite being used by only 3 fishermen. This suggests a high efficiency of this gear type in yielding substantial catches. In contrast, Gear ID 20, used by the most significant number of fishermen (14), covered the most extensive area (2,484.8 hectares) but resulted in a considerably lower total catch volume (3,202.4 kgs).

Gear IDs 9 and 2 also showed exciting patterns. Gear ID 9, used by 9 fishermen, covered a moderate area and yielded a substantial catch of 1,825.5 kgs. Conversely, Gear ID 2, despite being used by 10 fishermen, resulted in a significantly lower catch (173.8 kgs) over a smaller area.

The least used gear, ID 26, employed by only 4 fishermen, covered the smallest area and yielded the lowest catch volume, indicating its limited effectiveness or specificity to certain fishing conditions.

The integration of local fishermen's knowledge was instrumental in interpreting these findings. Their insights provided vital context to understand the efficiency of different gear types in various environmental conditions. Complemented by the fishermen's expertise, the data-driven approach enabled a nuanced understanding of the fishing zones and gear effectiveness.

This study illustrates the synergy of advanced computational methods and traditional fishing knowledge, highlighting the need for a balanced approach incorporating technological and local expertise in fisheries management. The analysis of gear types, area coverage, and catch volumes provides a comprehensive understanding of the dynamics in play, underscoring the importance of tailored strategies in fisheries management.

Table 3. *Analysis of Gear Type Effectiveness*

Gear_id	Total Area (hectare)	Total Caught (kg)	No. of Fisherman
7	2,081.6	15,958	3
20	2,484.8	3,202.4	14
9	338.2	1,825.5	9
2	224.1	173.8	10
26	18.8	80	4

Insights for Fishermen

A thorough analysis of species distribution and catch data provided significant insights for fishermen. 'Species ID 1' was the most predominant, with an impressive total catch of 3,924.2 kilograms, followed by Species IDs 56, 78, 31, and 21, as indicated in Table 4.

Table 4. *Predominant Fish Species and Their Total Catch*

Species ID	Total catch in kilograms
1	3,924.2
56	2,491.4
78	1,968.5
31	1,479.9
21	1,407
82	1,301.8
109	843.9
77	744
116	664.5
117	621

In Table 5, the monthly data reveals Species 1's peak catches in March (1016.2 km) and May (1462.5 km), along with notable catches in February (854 km) and July (304.5 km). Species 56, with a peak catch in January (1290.5 km) and a strong presence in June (454.9 km), emerges as another important species for targeted fishing.

Species 77 peaks in February (421 km), suggesting this is an optimal month for targeting this species. Species 78, with significant catches in July (62 km), September (128 km), October (285 km), and December (171.5 km), offers several periods for targeted fishing. Other species, such as 31 and 21, consistently appear in top catches across multiple months, indicating their potential as steady fishing targets.

Fishermen are, therefore, recommended to focus on Species 1 throughout the year, with additional emphasis on Species 56, 77, and 78 during their respective peak months to maximize their catch. This strategic approach is guided by observed catch patterns and promotes sustainable fishing practices.

Table 5. *Monthly Peak Catches for Key Species*

Month	Recommended Species (IDs)	Catch (kilograms)
January	56, 109, 1, 108, 77	1290.5, 642, 187, 106.5, 106
February	1, 77, 116, 61, 56	854, 421, 408.5, 214.8, 124
March	1, 117, 120, 82, 119	1016.2, 545, 515.5, 233.5, 202
April	31, 121, 25, 32, 24	152.4, 67, 45.7, 37.6, 36.8
May	1, 116, 56, 31, 121	1462.5, 256, 160, 142.4, 35
June	21, 56, 66, 31, 49	883, 454.9, 214, 114.1, 102.6
July	1, 31, 121, 27, 78	304.5, 99.9, 74.5, 64.7, 62
August	21, 77, 31, 27, 63	161, 110, 97.2, 58.1, 42.4
September	82, 78, 21, 56, 31	180, 128, 108, 61, 57.3
October	78, 31, 27, 85, 115	285, 53.5, 44.5, 32, 28
November	21, 77, 31, 27, 63	161, 110, 97.2, 58, 42.5
December	56, 31, 78, 38, 82	317, 197.6, 171.5, 71.4, 46.3

Accuracy Evaluation Compared to Commercial GPS Devices

Evaluating IoT device efficacy through geolocation accuracy compared to commercial GPS devices was pivotal in this research. The aim was to analyze the previously estimated 5% variance in accuracy, notably in diverse environmental settings like open areas and mangrove-rich regions, including the impact of weather conditions on Received Signal Strength Indicator (RSSI) values.

Concurrent data collection from both the IoT and commercial-grade devices at identical locations enabled a comprehensive assessment of performance variance under varying environmental conditions. Meticulous comparison of coordinates from each device type, highlighted disparities or consistency in performance across these environments with a specific focus on how weather conditions affect the RSSI.

Figure 13 presents variances between the IoT devices and commercial counterparts. The impact of weather conditions on network signal strength was evident. For example, in dense mangroves and during adverse weather conditions, IoT devices relying primarily on 2G signals showed fluctuating RSSI values, affecting data transmission reliability. This is indicated by red dots, marking positions where the IoT devices in challenging environments like dense mangroves experienced reduced signal strength. In contrast, commercial devices, which in similar conditions often maintained more stable 3G signals, are represented by green dots in open areas with clear weather conditions, indicating locations where IoT devices consistently achieved stronger 3G signals, ensuring reliable data transmission.

Sensitivity and calibration of the GSM modules in IoT devices were recognized as factors contributing to the variance, exacerbated by weather conditions affecting signal strength. Therefore, a focus on continuous calibration and enhancements is essential, with future improvements to include advanced GSM modules and algorithmic adjustments to decrease variance and improve resilience to weather-induced signal fluctuations. These initiatives balance cost-efficiency and precision, making the system practical for fisheries management where commercial devices are not feasible.

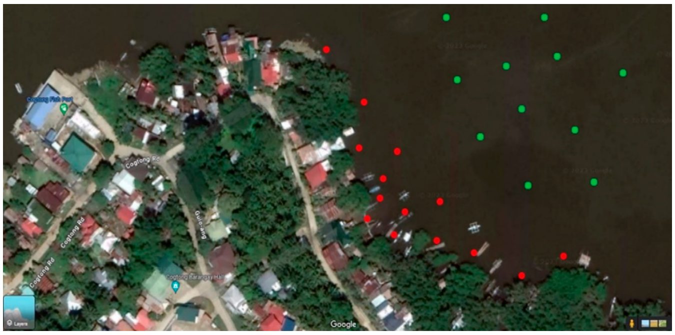


Figure 13. *Comparison of IoT Device Signal Strength with 2G and 3G Indicators*

IoT Device Geolocation Tracking Performance in Variable Signal Environments

The performance of the IoT-based geolocation tracking system was critically dependent on the cellular network signal strength and reliability, which in turn was influenced by weather conditions. To evaluate this, we conducted tests in environments with contrasting network conditions — mangrove-dense areas with 2G network limitations and open sea areas with stronger 3G network signals, under various weather scenarios.

As shown in Table 6, the tests revealed significant variations in data transmission intervals and success rates, correlating with the network type, signal strength (RSSI), and prevailing weather conditions. In mangrove areas, especially during poor weather, the weaker 2G network led to inconsistent transmission schedules and lower success rates due to reduced RSSI values. In contrast, the open sea areas, typically with more stable weather, showed improved transmission regularity and higher success rates, attributed to stronger 3G network signals and higher RSSI values.

The variation emphasizes the importance of considering environmental factors and network infrastructure when deploying IoT systems in maritime settings, especially the impact of weather on signal strength. Our findings suggest prioritizing areas with stable 3G network coverage and employing adaptive technologies for consistent data transmission across varying network signals and weather conditions for reliable IoT-based marine data collection.

Table 6. *IoT Geolocation Data Transmission Intervals Under Diverse Network Conditions*

BoatID	Latitude	Longitude	Timestamp	RSSI	Success	Network
1	9.8402572	124.5314185	2023-08-01 06:15:49	-101	NO	2G
1	9.8402829	124.5314403	2023-08-01 06:18:51	-89	Yes	2G
1	9.8403074	124.5314577	2023-08-01 06:21:55	-97	No	2G
1	9.8403543	124.5315080	2023-08-01 06:24:60	-99	No	2G
1	9.8403834	124.5315107	2023-08-01 06:27:60	-81	Yes	2G
1	9.8404342	124.5315322	2023-08-01 06:30:13	-97	No	2G
1	9.8405307	124.53158249	2023-08-01 06:33:25	-73	Yes	3G
1	9.8405908	124.53161468	2023-08-01 06:36:19	-70	Yes	3G
1	9.8406206	124.53170319	2023-08-01 06:39:46	-65	Yes	3G
1	9.8407249	124.53183261	2023-08-01 06:42:47	-68	Yes	3G
1	9.8407520	124.53196001	2023-08-01 06:45:50	-67	Yes	3G
1	9.8410296	124.53214144	2023-08-01 06:48:55	-64	Yes	3G

Note: RSSI values are reported in dBm. Lower numbers indicate stronger signals. "Success" indicates whether the data transmission was successful.

Fishing Gear Effectiveness Analysis

In our examination of fishing gear effectiveness, significant variations in catch volumes were identified across different gear types under varied environmental conditions. As summarized in Table 7, this data delineates these variations and highlights trends in gear performance relative to specific weather conditions and temperatures. Notably, Gear ID 7 demonstrated remarkable efficiency in overcast conditions and light rain. This analysis underlines the nuanced relationship between fishing gear selection and environmental conditions, providing valuable insights for optimizing catch yields in various weather scenarios.

This analysis demonstrates the nuanced interplay between fishing gear selection and environmental conditions, providing valuable insights for optimizing catch yields in varying weather scenarios.

Table 7. *Summary of Fishing Gear Effectiveness Under Various Weather Conditions*

Gear ID	Total Catch (kilograms)	Average Temperature (°C)	Weather Condition
7	4,011.7	28.37	Overcast Clouds
7	3,809.4	27.63	Light Rain
7	2,233.5	28.48	Broken Clouds
2	177.6	27.92	Overcast Clouds

Table 7. *(continued)*

Gear ID	Total Catch (kilograms)	Average Temperature (°C)	Weather Condition
2	93.9	27.97	Broken Clouds
9	229.1	28.62	Broken Clouds
1	70	27.65	Overcast Clouds
7	1,644.4	28.34	Few Clouds
3	32	28.70	Moderate Rain
6	4	27.75	Moderate Rain

Algorithm Accuracy Evaluation

The primary objective was to ascertain the accuracy of the Graham Scan method in representing real-world fishing yields. Experts from the Bureau of Fisheries and Aquatic Resources (BFAR) were selected for this evaluation, as their deep understanding of fishing zones and activities would provide valuable insights into the algorithm's effectiveness.

Table 8 presents the outcomes of our interface evaluation. Key usability aspects such as design and visualization, navigation and functionality, and learnability and help resources were scrutinized, yielding impressive ratings. The dashboard's layout, color themes, text clarity, and visual elements scored a high at 4.6. Navigation ease and functionality received a 4.4, and the dashboard's learnability and availability of help resources were rated at 4.5. These results indicate an overall satisfactory user experience with an average usability rating of 4.5, underscoring the dashboard's user-friendly design.

Table 8. *Interface Evaluation Outcome*

Usability Test Areas	Rating
Design and Visualization (Dashboard layout, color themes, text clarity, tabs, interactive elements, visual representations)	4.6
Navigation and Functionality (Navigating between dashboard sections, selecting options, locating tools and features)	4.4
Learnability and Help Resources (Grasping the provided guidelines, recalling features, generating visual data, Feedback Loop)	4.5

In our comprehensive evaluation detailed in Table 9, the Graham Scan algorithm's effectiveness in fisheries management, was rigorously examined. This assessment utilized the advanced spatial analysis capabilities of Turf.js, a JavaScript library designed for geospatial operations, along with GeoJSON-formatted data. Turf.js is particularly adept at processing and analyzing spatial data, facilitating operations such as area measurement, centroid calculation, and polygon intersection.

For this evaluation, we rigorously compared the polygons generated by the Graham Scan algorithm with actual ground truth areas derived from in-field GPS data. These real-world data points were meticulously collected from the fishing activities of Fisherman 10, providing an accurate representation of active fishing zones. By tracking these zones via GPS during regular fishing operations and converting them into GeoJSON format, we established a factual basis for evaluating the algorithm's performance.

The analysis focused on the degree of similarity between the algorithm-generated polygons and the actual ground truth areas. We observed a high degree of accuracy in the algorithm's polygon formation, as evidenced by the close match between the area outlined by the Graham Scan algorithm (1,188.77 ha.) and the area derived from Fisherman 10's GPS data (1,519.11 ha.). The overlapping area of (1,164.55 ha.) further highlighted the algorithm's precision. Moreover, the minimal centroid distance of

0.409 kilometers between the algorithm-generated and actual ground truth polygons underscored the algorithm's precision in representing geolocation points within the convex hull.

Most notably, the overlap percentage of 97.96% in spatial-temporal data signifies the Graham Scan algorithm's exceptional proficiency in synchronizing spatial and temporal data, thus confirming its utility in accurately mapping fishing zones. As depicted in Figure 14, these findings show Fisherman 10's spatial data in red and the ground truth data in green, affirming the Graham Scan algorithm's vital role in fisheries management. They showcase its robustness and reliability for comprehensive spatial and temporal analysis, ensuring that the algorithm is theoretically sound and practically effective in real-world scenarios.

Table 9. *Algorithm Accuracy Evaluation Outcome*

Test Areas	Results
Graham Scan Polygon Formation Accuracy	
Area of Algorithm Polygon	1,188.77 ha.
Area of Ground Truth Polygon	1,519.11 ha.
Overlapping Area	1,164.55 ha.
Representation of Geolocation Points within Convex Hull	
Distance Between Centroids	0.409 Km
Accuracy Assessment in Spatial-Temporal Data	
Overlap Percentage (Based on Algorithm Polygon)	97.96%

Figure 14. *Comparative Visualization of Graham Scan Algorithm Output and Ground Truth Data from Fisherman 10's GPS Tracking*

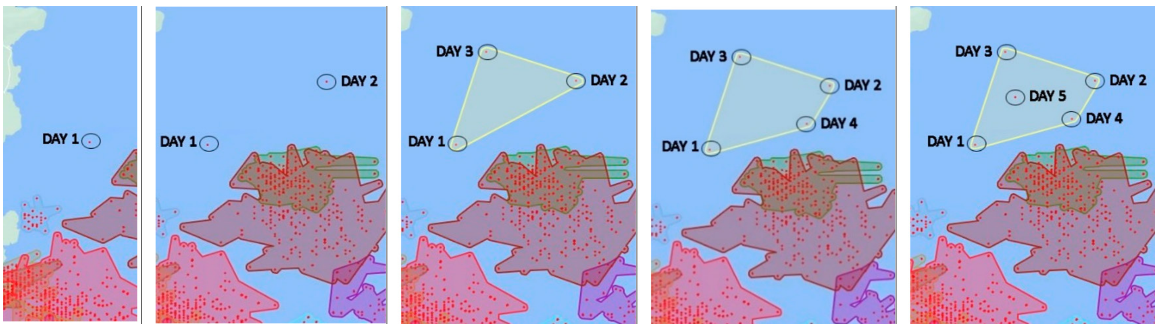


Figure 15. *Five-Day Graham Scan Algorithm Testing Outcomes*

During the testing phase, as depicted in Figure 15, the algorithm's capability was further substantiated through a five-day real-world validation process. IoT devices onboard fishing boats collect geolocation data daily, which the Graham Scan algorithm processed to form and adjust the convex hulls dynamically. This continuous data collection tested the algorithm's consistency and resilience and its adaptability to the environmental variables and operational conditions typical in marine settings. The positive outcome of this validation process attests to the algorithm's robustness and its applicability for enhancing fisheries management practices.

Operational Effectiveness and Usability Testing

Following the algorithm accuracy evaluation, a thorough usability testing of the web and mobile application, iGAT 2.x (Interactive Geocoded-fisheries Assessment Tools), was conducted from August 1 to August 5, 2023. This phase was crucial for gathering feedback from end-users to refine the application's features. A diverse group of participants, including fishermen, fisheries management personnel, application program testers, and other key stakeholders, were involved in this real-world setting test.

During this period, users interacted with the application, executing tasks that mirrored their daily fishing and management activities. This hands-on experience provided valuable insights into user behavior, the ease of navigation within the application, and overall user engagement. Participants generally found the application intuitive and user-friendly, quickly adapting to its various functionalities. However, they also highlighted areas needing improvement, such as the requirement for more detailed help resources for certain complex features.

Feedback gathered during these sessions was pivotal in guiding subsequent enhancements. Suggestions for improving the dashboard's interactivity and adding customizable features to cater to the varying needs of different user groups were particularly influential. In response to this feedback, the application underwent significant updates. These updates included refining the dashboard layout for clearer data visualization and introducing a feature for customizing data displays according to individual preferences.

A notable update was the inclusion of more comprehensive reporting tools within the application, addressing user feedback that underscored the importance of such features for effective management and decision-making. Following these enhancements, the application was retested with the same group of end-users, who expressed greater satisfaction with the improved functionality, particularly the expanded reporting capabilities.

This iterative process of usability testing, incorporating direct user feedback, and refining the application underscores our commitment to developing tools that are not only technologically advanced but also practical and user-friendly for the fishing community. As a result, iGAT 2.x has emerged as a valuable asset in fisheries management, enabling users to make informed decisions based on real-time data and thorough analysis.

The comprehensive testing of our application yielded overwhelmingly positive results, reflecting its effectiveness and user-friendliness. An impressive 91% of testers rated the application as highly user-friendly and accurate, a testament to its intuitive design and reliable performance. This feedback is invaluable for the ongoing refinement and enhancement of the application, ensuring that it continues to effectively meet and exceed the evolving needs of its users.

Additionally, a notable outcome of our research was the high accuracy level achieved by the Graham Scan algorithm. The algorithm demonstrated an impressive overlap percentage of 97.96% in spatial-temporal data analysis. This high accuracy rate underscores the algorithm's capability in accurately mapping fishing zones and representing geolocation points within the convex hull, further affirming its vital role in effective fisheries management.

Such high user satisfaction rates, combined with the remarkable accuracy of the Graham Scan algorithm, underscore the application's significant potential as an indispensable tool in fisheries management. Its capability to facilitate informed decision-making among fishermen, underpinned by real-time data and thorough analysis, positions it as a crucial asset in sustainable fisheries practices and data-driven management strategies.

These outcomes, marked by high user satisfaction and algorithmic accuracy, underline the application's potential as an indispensable tool in fisheries management. As reported by Anuchiracheeva et al., integrating local ecological knowledge with scientific tools like GIS has significantly enhanced fisheries management in regions such as Southeast Asia. The success of our application echoes these findings and demonstrates the potential for technology-driven solutions to enhance informed decision-making, supported by real-time data and in-depth analysis, making it a vital asset for sustainable fisheries and data-driven strategies. This aligns with the global push towards more adaptive, localized, and sustainable fishing practices, suggesting that our application could serve as a model for future technological integrations in fisheries management worldwide.

CONCLUSION

This research effectively utilized the Graham Scan method in marine analytics, notably achieving the primary objective of identifying key fishing zones. The iGAT 2.x application, central to this study, underwent rigorous testing, and its results demonstrated robust functionality and user-friendliness. This was supported quantitatively by solid usability scores (average of 4.52) and a high acceptance rate (91%) from the marine community, indicative of its practical application in real-world settings.

Our analysis uncovered significant variations in the effectiveness of different fishing gears under varied environmental conditions. A key finding was the superior effectiveness of Gear ID 7 in certain weather patterns, suggesting that adapting gear choices based on weather forecasts could enhance fishing efficiency and promote sustainable practices.

Despite these achievements, we encountered challenges, including the absence of comprehensive boat trajectory data and minor discrepancies in geolocation accuracy. These areas highlight opportunities for future enhancements. Upcoming research efforts will focus on integrating more extensive oceanic data and improving the mobility and robustness of our technological solutions.

A promising direction for future exploration is the adoption of AI for predictive modeling in fisheries management. AI's potential to revolutionize the prediction and understanding of fishing zones is significant. However, the effectiveness of AI models is contingent upon the availability of extensive data. Our current data scope is somewhat limited for fully leveraging AI algorithms. Thus, a strategic effort to collect a more comprehensive dataset is crucial for the development and validation of precise AI models.

Further, we recognize the importance of engaging with the local community and authorities in our research efforts. We plan to conduct orientation seminars and workshops for stakeholders such as fish port officers and fishermen in collaboration with the LGU of Candijay. These sessions aim to disseminate the findings of our study, provide training on the use of the iGAT 2.x app, and promote responsible fishing practices aligned with sustainable fisheries management.

In conclusion, while this study lays a solid foundation for more informed and sustainable fishing strategies, there remains a significant avenue for additional research and development. The integration of environmental factors with cutting-edge technological advancements continues to be a pivotal aspect of enhancing fisheries management strategies. Through continued research, collaboration, and technological innovation, we aim to contribute to the sustainable development of the fishing industry.

REFERENCES

Agcaoili, S. (2018). Geographic Information System-Based Suitability Analysis for Potential Shallow Tube-Well Irrigation Development. *Recoletos Multidisciplinary Research Journal, 6*(2), 35-49. https://doi.org/10.32871/rmrj1806.02.04

Anuchiracheeva, S., Demaine, H., Shivakoti, G., & Ruddle, K. (2003). Systematizing local knowledge using GIS: fisheries management in Bang Saphan Bay, Thailand. *Ocean & Coastal Management, 46*(11-12), 1049-1068. https://doi.org/10.1016/j.ocecoaman.2004.01.001

Bradley, D., Merrifield, M., Miller, K., Lomonico, S., Wilson, J., & Gleason, M. (2019). Opportunities to improve fisheries management through innovative technology and advanced data systems. *Fish and Fisheries, 20*(3), 564-583 https://doi.org/10.1111/faf.12361

Calderwood, J. (2022). Smartphone application use in commercial wild capture fisheries. *Reviews in Fish Biology and Fisheries, 32*, 1063-1083. https://doi.org/10.1007/s11160-022-09727-6

Coutinho, R. W. L., & Boukerche, A. (2022). Towards a Novel Architectural Design for IoT-Based Smart Marine Aquaculture. *IEEE Internet of Things Magazine, 5*(3), 174-179. https://doi.org/10.1109/IOTM.001.2200065

Dash, M. K., Singh, C., Panda, G., & Sharma, D. (2023). ICT for sustainability and socio-economic development in fishery: a bibliometric analysis and future research agenda. *Environmental Development and Sustainability, 25*, 2201-2233. https://doi.org/10.1007/s10668-022-02131-x

De Freitas, D., & Tagliani, P. R. (2009). The use of GIS for the integration of traditional and scientific knowledge in supporting artisanal fisheries management in southern Brazil. *Journal of Environmental Management, 90*(6), 2071-2080. https://doi.org/10.1016/j.jenvman.2007.08.026

Gladju, J., Kamalam, B. S., & Kanagaraj, A. (2022). Applications of data mining and machine learning framework in aquaculture and fisheries: A review. *Smart Agricultural Technology, 2*, 100061. https://doi.org/10.1016/j.atech.2022.100061

Jeyanathan, J. S., Kumar, K. N., Reddy, P. V., Chaithanya, C. V., Kumar, M. N., & Manikandan, P. (2023). GPS Assistive Communication Tool for Fishermen Community using Internet of Things. *2023 8th International Conference on Communication and Electronics Systems (ICCES)*, 361-364. https://doi.org/10.1109/ICCES57224.2023.10192755

Khatuwal, V. S., & Puri, D. (2022). Business Intelligence Tools for Dashboard Development. *2022 3rd International Conference on Intelligent Engineering and Management (ICIEM)*, 128-131. https://doi.org/10.1109/ICIEM54221.2022.9853086

Kolding, J., Béné, C., & Bavinck, M. (2014). Small-scale fisheries: Importance, vulnerability, and deficient knowledge. *Governance of Marine Fisheries and Biodiversity Conservation: Interaction and Co-evolution*, 317-331. https://doi.org/10.1002/9781118392607.ch22

Lamot, M., & Žalik, B. (2003). A fast polygon triangulation algorithm based on uniform plane subdivision. *Computers & Graphics, 27*(2), 239-253. https://doi.org/10.1016/S0097-8493(02)00281-9

Leleu, K., Alban, F., Pelletier, D., Charbonnel, E., Letourneur, Y., Boudouresque, C. (2012). Fishers' perceptions as indicators of the performance of Marine Protected Areas (MPAs). *Marine Policy, 36*(2), 414-422. https://doi.org/10.1016/j.marpol.2011.06.002

Morzaria-Luna, H. N., Turk-Boyer, P., Polanco-Mizquez, E., Downton-Hoffman, C., Cruz-Piñón, G., Carrillo-Lammens, T., Loaiza-Villanueva, R., Valdivia-Jiménez, P., Sánchez-Cruz, A., Peña-Mendoza, V., Montserrat López-Ortiz, A. M., Koch, V., Vázquez-Vera, L., Arreola-Lizárraga, J. A., Amador-Castro, I., Castillo, A., & Munguia-Vega, A. (2020). Coastal and Marine Spatial Planning in the Northern Gulf of California, Mexico: Consolidating stewardship, property rights, and enforcement for ecosystem-based fisheries management. *Ocean & Coastal Management*, 105316. https://doi.org/10.1016/j.ocecoaman.2020.105316

Musembi, P., Fulanda, B., Kairo, J., Githaiga, M. (2019). Species composition, abundance and fishing methods of small-scale fisheries in the seagrass meadows of Gazi Bay, Kenya. *Journal of the Indian Ocean Region, 15*(2), 139-156. https://doi.org/10.1080/19480881.2019.1603608

Ong, S. P., Cholia, S., Jain, A., Brafman, M., Gunter, D., Ceder, G., & Persson, K. (2015). The Materials Application Programming Interface (API): A simple, flexible, and efficient API for materials data based on REpresentational State Transfer (REST) principles. *Computational Materials Science, 97*, 209-215. https://doi.org/10.1016/j.commatsci.2014.10.037

Patil, P., & Sachapara, V. (2017). Providing smart agricultural solutions/techniques by using Iot based toolkit. *2017 International Conference on Trends in Electronics and Informatics (ICEI),* 327-331. https://doi.org/10.1109/ICOEI.2017.8300942

Sharif, M., Naqvi, S. Z., Raza, M., & Haider, W. (2012). A new Approach to Compute Convex Hull. I*nnovative Systems Design and Engineering, 2*(3).

Tilley, A., Dos Reis Lopes, J., & Wilkenson, S. (2020). PeskAAS: A near-real-time, open-source monitoring, and analytics system for small-scale fisheries. *PLoS One, 15*(11), e0234760. https://doi.org/10.1371/journal.pone.0234760

Wang, X., Zhou, X., & Wang, S. (2012). Summarizing Large-Scale Database Schema Using Community Detection. *Journal of Computer Science and Technology, 27,* 515-526. https://doi.org/10.1007/s11390-012-1240-1

How to cite this article:
Amora E. N., & Cuizon, J. (2024). Utilizing IOT and Geospatial Analytics for Sustainable Fisheries Management. Recoletos Multidisciplinary Research Journal 12(1), 195-214. https://doi.org/10.32871/rmrj2412.01.15