

# GIS-BASED SHRIMP FISHERY SUPPLY CHAIN SYSTEM MODEL USING GETIS-ORD GI\* AND ANT COLONY OPTIMIZATION ALGORITHMS

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## ABSTRACT

Shrimp fisheries production is one of the leading commodities of the aquaculture sector in the North Aceh coastal region of Indonesia, which plays a vital role in supporting the economy of coastal communities. Information on production distribution patterns and supply chain efficiency is still limited, requiring spatial-based analysis to support decision-making. This study aims to identify areas of concentrated shrimp production using the Getis-Ord Gi\* method and optimize the supply chain using the Ant Colony Optimization algorithm. This study was conducted in 22 sub-districts spread across Bireuen, North Aceh, and East Aceh Regencies with a total Vannamei Shrimp production of 6,231.29 tons per year. The Getis-Ord Gi\* analysis results indicate that Nurussalam District was identified as a hotspot with a GiZScore of 2.2946 and a p-value of 0.0218, while Lapang and Baktiya Barat Districts were identified as coldspots with a GiZScore of -2.3479 and a p-value of 0.0189. The remaining 19 sub-districts were in the not-significant category. Furthermore, supply chain optimization was carried out on 61 ponds connected to three main storage points, namely Peudada Fish Landing Base, Krueng Mane Fish Landing Base and Idi Fishery Port. The results of the Ant Colony Optimization algorithm application showed that the total distribution distance could be reduced from 1905.92 km to 1905.60 km, resulting in a distance saving of 0.32 km with an efficiency level of 0.02%. In addition, Peudada District had the lowest distribution cost value of 1.39 km, while Nurussalam District as a hotspot area had a distribution cost value of 16.07 km. The results of the study showed that the integration of the Getis-Ord Gi\* method and the Ant Colony Optimization algorithm based on the Geographic Information System was able to identify priority production areas and produce more efficient distribution channels to support the development of the Vannamei Shrimp supply chain in the North Coast region of Aceh, Indonesia.

**Keywords:** *Ant Colony Optimization (ACO), Getis-Ord Gi\*, Supply Chain, Shrimp Fisheries, Geographic Information System.*

## 1. INTRODUCTION

The fisheries sector is a strategic sector in national economic development, particularly in coastal areas where capture fisheries and aquaculture are the primary sources of livelihood. Fisheries not only contribute to the national food supply but also play a role in increasing community income, creating jobs, and strengthening the coastal economy (Ministry of Maritime Affairs and Fisheries (KKP)) [1]. One aquaculture commodity with high economic value is Vannamei Shrimp (*Litopenaeus vannamei*), which in recent years has become a leading Indonesian export commodity due to its high productivity and increasing market demand [2].

The North Coast of Aceh, Indonesia, holds significant potential for shrimp aquaculture

development. Vannamei Shrimp is a leading commodity in Aceh's aquaculture sector, boasting high economic value and growing market demand [3]. The advantages of Vaname shrimp, such as relatively rapid growth and high productivity, make it a strategic commodity for supporting the economic growth of coastal communities [4]. However, this significant potential has not been matched by the availability of accurate spatial information regarding the distribution of pond locations and production levels of Vaname shrimp. Production data is still presented in tabular and administrative form, thus lacking a comprehensive depiction of spatial patterns of production concentration [5]. This situation limits the ability to determine priority areas for fisheries development based on spatial data. The

large potential for Vannamei Shrimp production has also not been fully matched by an optimal management and distribution system [6], [7].

One of the main challenges in developing Vannamei Shrimp fisheries is the lack of comprehensive spatial information on the distribution of shrimp production areas and their linkages to the supply chain. Vannamei Shrimp fisheries are often unevenly distributed, complicating distribution planning and logistics decision-making. This situation results in high distribution costs, delivery delays, and reduced product quality due to inefficient travel times. The use of Geographic Information Systems (GIS) is one solution to address these issues, as it integrates spatial and non-spatial data to visually and analytically map potential fishery areas [8], [9], [10].

However, conventional mapping is insufficient to identify in-depth spatial patterns of production. Therefore, a spatial statistical approach using the Getis-Ord method is needed, which is capable of identifying hotspots and coldspots in Vannamei Shrimp production areas based on intensity and proximity. Furthermore, fisheries supply chain issues are not only related to production locations but also to determining efficient distribution channels. The ACO algorithm is an artificial intelligence-based optimization method inspired by the behavior of ants in finding the shortest path [11], [12], [13]. This algorithm is effective in solving path optimization problems and is highly relevant for application in fishery product distribution systems [14], [15], [16].

Based on these issues, a mapping model for Vannamei Shrimp fisheries and supply chain pathways is needed, integrated with a spatial approach and optimization algorithm. The integration of the Getis-Ord method and the GIS-based ACO algorithm is expected to produce accurate information regarding potential production areas and optimal supply chain pathways. This study aims to develop a GIS-based mapping model for Vannamei Shrimp fisheries and supply chain pathways by integrating the Getis-Ord spatial statistics method and the Ant Colony Optimization (ACO) algorithm. The Getis-Ord method is used to identify spatial patterns and determine hotspots and coldspots in Vannamei Shrimp production areas based on production data and pond locations. The Ant Colony Optimization algorithm is applied to optimize the supply chain pathway from production areas to distribution points by considering distance, travel time, and distribution costs. It is hoped that the integration of the two methods will produce

production mapping and supply chain optimization models that are more accurate and applicable.

## 2. LITERATURE REVIEW

The state of the art and novelty of this research are based on the results of previous research conducted by the lead researcher and several other related studies. Previous research conducted by Nurdin et al. [17] the lead researcher included research on model of information system for mapping and clustering agricultural and agricultural products production based on Geographic Information Systems (GIS). The results of this research can be used for planning agricultural and agricultural products supply chain systems. Research conducted by other researchers related to this research, Huang et al. [18] the supply chain in the digital economy is very important in managing the flow of goods and services from suppliers to consumers; Artificial intelligence can significantly improve demand forecasting and supply chain operations [19].

Li et al. [20] this paper addresses the problem of optimizing perishable agricultural products during transportation from the perspective of sustainable development, and constructs a complete transportation route optimization scheme. By analyzing the characteristics of perishable agricultural products, their influencing factors during transportation, and the current research status, this study proposes an optimization model based on the ant colony algorithm and outlines its solution method. Lahdhiri et al. [21] the application of the Ant Colony Optimization (ACO) model in textile logistics, using case studies and computer modeling, resulted in significant cost savings and improved service levels in the industry. In practice, ACO theory improves the efficiency, flexibility, and environmental sustainability of supply chain transportation, providing a competitive advantage for the textile industry in emerging markets. In logistics, ACO has proven effective in determining optimal distribution routes, reducing transportation costs, and minimizing travel time. Recent research shows that ACO can increase distribution route efficiency by up to 30–40% compared to classical methods such as Dijkstra or Greedy [22], [23].

Kim and Park [24], the Getis-Ord  $G_i^*$  method is widely used to spatially identify areas with high levels of fisheries production or activity. Recent research has shown that this method is one of the most accurate techniques for identifying GIS-based fisheries commodity distribution patterns, especially when combined with satellite imagery and regional statistical data. Mohamadi et al. [25] this study aims

to determine groundwater quality indicators and assess them through hotspot analysis and hotspot accumulation, GIS-based hotspot analysis (HA) applying Getis-Ord  $G_i^*$  statistics was used. Hotspot accumulation analysis was launched to identify the Groundwater Quality Index (AHA-GQI). In addition, the Schuler method (AHA-SM) was used to determine the maximum level (ML) for the hottest hotspot and the lowest level (LL) for the coldest hotspot, as well as the compound level (CL). The results showed that there was a significant correlation ( $r = 0.8$ ) between GQI and SM. However, the correlation between GQI and nitrate was not significant and the correlation between SM and nitrate was very low ( $r = 0.298$ ,  $\text{sig} > 0.05$ ).

GIS enables the integration of spatial and non-spatial information into a unified analytical framework, thereby facilitating spatial decision-making processes [26]. The application of GIS has grown rapidly in various sectors, including agriculture, environmental monitoring, urban planning, disaster management, and fisheries. In fisheries and aquaculture, GIS has been widely utilized to assess aquaculture suitability, monitor production distribution, evaluate environmental conditions, and support regional development planning [27], [28].

Based on the above research, the proposed study differs from previous studies, particularly in the methods, case studies, and data used. Previous research by the principal investigator also differed in the methods used and the resulting models. This study proposes a novel research approach in the form of a mapping system and supply chain model for shrimp fishery production areas using the Getis-Ord  $G_i^*$  and Ant Colony Optimization Algorithm approach based on Geographic Information Systems.

### 3. RESEARCH METHODOLOGY

#### 3.1 Getis-Ord $G_i^*$ Hotspot Analysis

The Getis-Ord  $G_i^*$  method is a spatial statistical technique used to identify hotspot and coldspot patterns in a region. This analysis aims to determine whether a phenomenon, such as fishery production or distribution, is significantly concentrated in a particular area. The  $G_i^*$  value indicates whether a location has a high concentration of values (hotspot) or low concentration (coldspot) compared to its surrounding areas [29]. This method evaluates local spatial autocorrelation by measuring the degree of spatial association between adjacent locations. The Getis-Ord  $G_i^*$  statistic is formulated as follows:

$$G_i^* = \frac{\sum_j^n 1 w_{ij} x_j - \sum_j^n 1 w_{ij} \bar{x}}{s \sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - (\sum_{j=1}^n w_{ij})^2}{n-1}}} \quad (1)$$

where:

$G_i^*$ : statistical value Getis-Ord  $G_i^*$  at location  $i$

$x_j$ : attribute value at location  $j$

$w_{ij}$ : spatial weight between locations  $i$  and  $j$

$\bar{x}$ : average attribute value

$S$ : standard deviation of attribute values

$n$ : total number of locations

#### 3.2 Ant Colony Optimization (ACO) Algorithm

To optimize shrimp distribution routes, this study implemented the Ant Colony Optimization algorithm. Colony Optimization algorithm is a metaheuristic optimization algorithm inspired by the foraging behavior of ant colonies in searching for the shortest path between food sources and nests [30]. The probability of selecting route  $j$  from node  $i$  by ant  $k$  is formulated as:

$$P_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta} \quad (2)$$

where:

$P_{ij}^k$  is the probability of selecting node  $j$ ;

$\tau_{ij}$  denotes pheromone intensity;

$\eta_{ij}$  represents heuristic visibility;

$\alpha$  and  $\beta$  are control parameters;

$N_i^k$  is the set of feasible nodes.

The colony optimization algorithm iteratively updates pheromone values based on route quality until an optimal or near-optimal distribution route is obtained. The optimization process aimed to minimize the total transportation distance between shrimp ponds and collection centers.

#### 3.3 Stages of Research

The research framework was designed to provide a systematic procedure for analyzing the spatial distribution of Vannamei Shrimp production and optimizing supply chain routes by integrating Geographic Information System (GIS), Getis-Ord  $G_i^*$  hotspot analysis, and Ant Colony Optimization (ACO). The overall research process consists of several sequential stages, including data acquisition, spatial database development, hotspot analysis, route optimization, web-based GIS implementation, and system evaluation.

The first stage involved collecting spatial and non-spatial datasets from various sources. Spatial data included administrative boundaries, road networks, shrimp pond locations, and collection center coordinates, while non-spatial data consisted

of shrimp production statistics and supporting attribute information. All datasets were verified, standardized, and integrated into a GIS database to ensure consistency prior to analysis.

The second stage focused on identifying statistically significant production clusters using the Getis-Ord Gi\* statistic. The hotspot analysis calculated GiZScore and  $p$ -value for each shrimp production location to determine hotspot and coldspot areas. Subsequently, the third stage applied the Ant Colony Optimization algorithm to determine efficient distribution routes connecting shrimp ponds and collection centers. Finally, all analytical outputs were integrated into a web-based GIS platform to support interactive visualization and decision-making processes. The steps taken in the research on mapping of shrimp fishery product areas and supply chain systems using the Getis-Ord Gi\* and Ant Colony Optimization algorithm are in Figure 1.

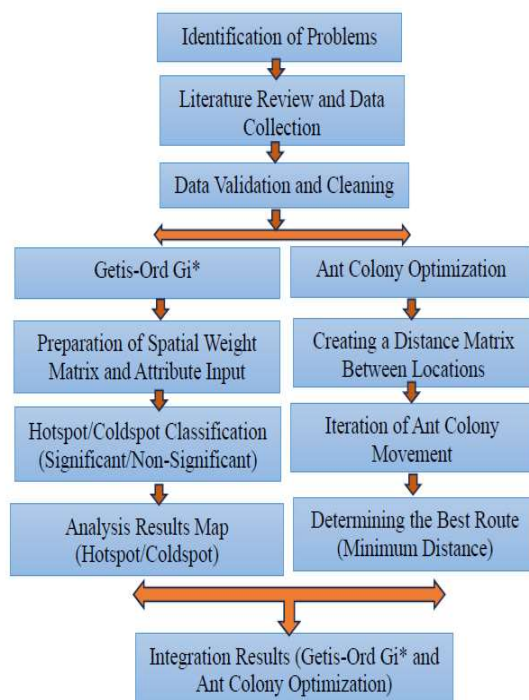


Figure 1: Stages and Research Procedure

### 3.4 Description of Research Data

This research data serves as the primary basis for mapping Vannamei Shrimp fishery areas and analyzing supply chain pathways in the northern coastal region of Aceh. The data used includes spatial and non-spatial information related to the location of Vannamei Shrimp production, production volume, pond distribution, collection points, road accessibility, and distribution routes to

marketing centers or supply chain destinations. All data was processed and analyzed using a Geographic Information System (GIS) to generate a spatial overview of Vannamei Shrimp production distribution patterns and support the identification of potential areas and optimal distribution pathways.

The Getis-Ord method was used to identify concentration patterns in areas with high and low Vannamei Shrimp production, while the Ant Colony Algorithm was used to analyze the most efficient supply chain pathways based on distance, accessibility, and interregional connectivity. Therefore, this research data description aims to explain the characteristics of the data used prior to conducting spatial analysis and distribution pathway optimization.

#### 3.4.1 Data on Vannamei Shrimp Production Results and Fishery Areas

In this study, production data and the location of Vannamei Shrimp fisheries were used to illustrate the distribution of pond production in the northern coastal region of Aceh, Indonesia. Production data were compiled by district and sub-district to demonstrate the contribution of each region to total Vannamei Shrimp production. Furthermore, location information was used as the basis for determining pond spatial locations, which were then analyzed in a GIS, including in identifying patterns of production area concentration using the Getis-Ord method. Vannamei Shrimp fishery production data and locations are presented in Table 1.

Table 1: Vannamei Shrimp Fishery Production Data Based on District and Sub-district

| District   | Subdistrict            | Production (Tons) |
|------------|------------------------|-------------------|
| Bireuen    | Jangka                 | 358,08            |
|            | Peudada                | 450,46            |
|            | Simpang Mamplam        | 386,09            |
|            | Gandapura              | 278,11            |
|            | Jeumpa                 | 219,12            |
|            | Kuala                  | 378,14            |
|            | Total Bireuen District | 2.070,00          |
| Aceh Utara | Dewantara              | 377,08            |
|            | Muara Batu             | 368,33            |
|            | Seuneudon              | 259,58            |
|            | Lapang                 | 165,86            |
|            | Bhaktiya Barat         | 134,16            |
|            | Jambo Aye              | 98,85             |

| District   | Subdistrict               | Production (Tons) |
|------------|---------------------------|-------------------|
|            | Samudra                   | 68,63             |
|            | Total Aceh Utara District | 1.472,49          |
| Aceh Timur | Julok                     | 352,80            |
|            | Peureulak                 | 68,23             |
|            | Darul Aman                | 133,94            |
|            | Simpang Ulim              | 302,20            |
|            | Bayeun                    | 197,90            |
|            | Madat                     | 632,60            |
|            | Peureulak Barat           | 543,15            |
|            | Peureulak Timur           | 199,05            |
|            | Nurussalam                | 258,93            |
|            | Total Aceh Timur District | 2.688,80          |

| District   | Number of Fishery Pond Location Points | Fishery Pond Location District                                                                                | Collection Point and Coordinates                    |
|------------|----------------------------------------|---------------------------------------------------------------------------------------------------------------|-----------------------------------------------------|
| Aceh Utara | 20                                     | Dewantara, Muara Batu, Seunuddon, Lapang, Baktiya Barat, T. Jamboe Aye, Samudera                              | Krueng Mane Fish Landing Base (5.250334, 96.909303) |
| Aceh Timur | 20                                     | Julok, Peureulak, Darul Aman, Simpang Ulim, Birem Bayeun, Madat, Peureulak Barat, Peureulak Timur, Nurussalam | Idi Fishing Port (4.959691, 97.773127)              |

### 3.4.2 Vannamei Shrimp Supply Chain Data

The Vannamei Shrimp fishery supply chain data in this study is used to explain the relationship between the location of the pond area as the point of origin of production and the catchment point as the initial distribution destination. This data includes district, sub-district, village, pond location coordinates, catchment area, and catchment point coordinates. This information is needed to build a distribution network in spatial analysis and serves as input for the supply chain optimization process using the Ant Colony Algorithm. The Vannamei Shrimp supply chain data is presented in Table 2.

Table 2: Vannamei Shrimp Supply Chain Data Based on Fishery Production Points and Collection Points

| District | Number of Fishery Pond Location Points | Fishery Pond Location District                             | Collection Point and Coordinates                |
|----------|----------------------------------------|------------------------------------------------------------|-------------------------------------------------|
| Bireuen  | 21                                     | Peudada, Jeumpa, Kuala, Jangka, Gandapura, Simpang Mamplam | Peudada Fish Landing Base (5.204606, 96.584287) |

## 4. RESULT AND DISCUSSION

### 4.1 Results of Production Hotspot Analysis Using Getis-Ord Gi\*

Production hotspot analysis using Getis-Ord Gi\* was conducted to determine the spatial concentration patterns of Vannamei shrimp production in the northern coastal region of Aceh. This method was used to identify sub-districts that tend to be high-production areas (hotspots), low-production areas (coldspots), and areas that do not show significant spatial patterns. The results of this analysis serve as the basis for understanding the characteristics of production distribution and support the process of determining regional priorities in the GIS-based supply chain optimization stage. The implementation results in z-scores and p-values that are used to determine the level of spatial significance. The results of the Getis-Ord Gi\* calculations are in Table 3.

Table 3: Getis-Ord Gi\* Calculation Results for Vannamei Shrimp Fishery Production

| District   | Subdistrict     | Production (Tons) | GiZScore | GiPValue | Category        |
|------------|-----------------|-------------------|----------|----------|-----------------|
| Bireuen    | Peudada         | 450,46            | 1,2800   | 0,2005   | Not Significant |
| Bireuen    | Jeumpa          | 219,12            | 0,9121   | 0,3617   | Not Significant |
| Bireuen    | Kuala           | 378,14            | 0,9121   | 0,3617   | Not Significant |
| Bireuen    | Jangka          | 358,08            | 0,6323   | 0,5272   | Not Significant |
| Bireuen    | Gandapura       | 278,11            | 1,1705   | 0,2418   | Not Significant |
| Bireuen    | Simpang Mamplam | 386,09            | 1,2800   | 0,2005   | Not Significant |
| Aceh Utara | Dewantara       | 377,08            | 0,3384   | 0,7350   | Not Significant |
| Aceh Utara | Muara Batu      | 368,33            | 1,1705   | 0,2418   | Not Significant |
| Aceh Utara | Seunuddon       | 259,58            | -1,5521  | 0,1206   | Not Significant |
| Aceh Utara | Lapang          | 165,86            | -2,3479  | 0,0189   | Coldspot        |
| Aceh Utara | Baktiya Barat   | 134,16            | -2,3479  | 0,0189   | Coldspot        |
| Aceh Utara | T. Jambo Aye    | 98,85             | -1,5521  | 0,1206   | Not Significant |
| Aceh Utara | Samudera        | 68,63             | -1,8280  | 0,0676   | Not Significant |
| Aceh Timur | Julok           | 352,80            | 0,7808   | 0,4349   | Not Significant |
| Aceh Timur | Peureulak       | 68,23             | -0,5075  | 0,6118   | Not Significant |
| Aceh Timur | Darul Aman      | 133,94            | -1,0302  | 0,3029   | Not Significant |
| Aceh Timur | Simpang Ulim    | 302,20            | 0,7808   | 0,4349   | Not Significant |
| Aceh Timur | Birem Bayeun    | 197,90            | -0,5075  | 0,6118   | Not Significant |
| Aceh Timur | Madat           | 632,60            | 0,7808   | 0,4349   | Not Significant |
| Aceh Timur | Peureulak Barat | 543,15            | 0,9736   | 0,3303   | Not Significant |
| Aceh Timur | Peureulak Timur | 199,05            | -0,5075  | 0,6118   | Not Significant |
| Aceh Timur | Nurussalam      | 258,93            | 2,2946   | 0,0218   | Hotspot         |

The results of hotspot and coldspot identification are obtained based on the z-score and p-value categories generated in the Getis-Ord Gi\* calculation process. Districts with positive and significant z-score values are categorized as

hotspots, while districts with negative and significant z-score values are categorized as coldspots. The summary of hotspot and coldspot identification results is shown in Table 4.

Table 4: Getis-Ord Gi\* Results Category Recapitulation

| Category        | Number of Subdistrict | Subdistrict                | GiZScore            | GiPValue           |
|-----------------|-----------------------|----------------------------|---------------------|--------------------|
| Hotspot         | 1                     | Nurussalam                 | 2,2946              | 0,0218             |
| Coldspot        | 2                     | Lapang and Baktiya Barat   | -2,3479             | 0,0189             |
| Not Significant | 19                    | 19 other subdistricts      | -1,8280 s.d. 1,2800 | 0,0676 s.d. 0,7350 |
| Total           | 22                    | All sub-districts analyzed | -                   | -                  |

#### 4.2 Visualisasi Peta Hotspot Berbasis GIS

GIS-based hotspot map visualization is used to spatially display the results of the Getis-Ord Gi\* analysis, allowing for clearer observation of the distribution patterns of hotspots, cold spots, and insignificant areas. In the GIS system, each sub-district is visualized with a different color category based on the analysis results, while pond and

catchment points are displayed as supporting elements in understanding the spatial relationships between production and the supply chain. The visualization of the Vannamei Shrimp production hotspot map is shown in Figure 2.

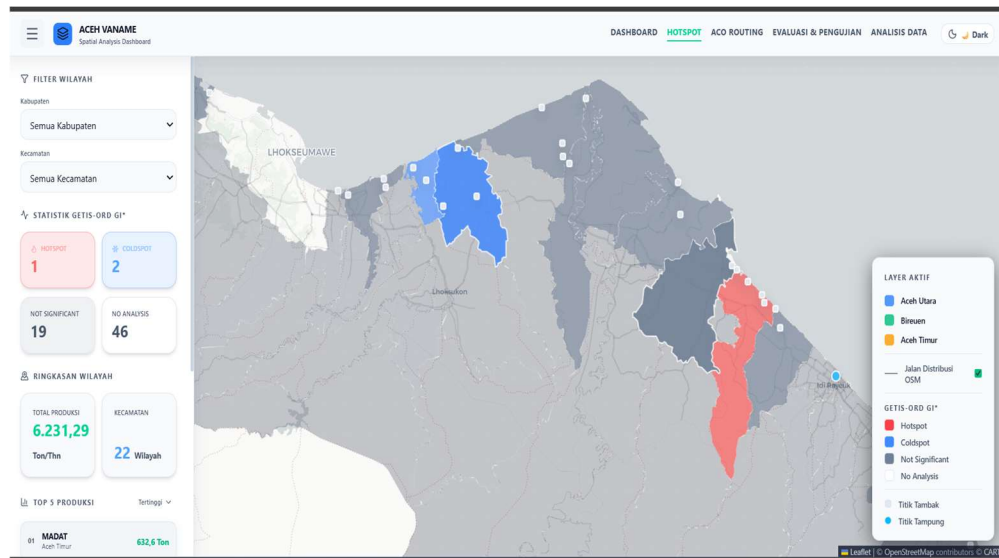


Figure 2: Visualization of Hotspot Maps of Vannamei Shrimp Production Results Based on GIS

#### 4.3 Supply Chain Optimization Results Using Ant Colony Optimization (ACO)

Supply chain optimization results are obtained based on the ACO cost values in each sub-district. Lower cost values indicate a relatively more efficient

route from the production area to the collection point, while higher cost values indicate accessibility barriers, longer travel distances, or sub optimal road network connectivity. The optimal supply chain path results based on the lowest ACO cost values are shown in Table 5.

Table 5: Optimal Supply Chain Path Results Based on ACO Cost Values

| Ranking | District   | Origin Node | Destination Node              | Production (Tons) | Gi* Status      | ACO cost value (Km) |
|---------|------------|-------------|-------------------------------|-------------------|-----------------|---------------------|
| 1       | Bireuen    | Peudada     | Peudada Fish Landing Base     | 450,46            | Not Significant | 1,39                |
| 2       | Aceh Utara | Muara Batu  | Krueng Mane Fish Landing Base | 368,33            | Not Significant | 2,26                |
| 3       | Bireuen    | Gandapura   | Peudada Fish Landing Base     | 278,11            | Not Significant | 6,46                |
| 4       | Bireuen    | Jeumpa      | Peudada Fish Landing Base     | 219,12            | Not Significant | 9,75                |
| 5       | Aceh Timur | Darul Aman  | Fishing Port Idi              | 133,94            | Not Significant | 10,71               |
| 6       | Aceh Utara | Dewantara   | Krueng Mane Fish Landing Base | 377,08            | Not Significant | 11,09               |
| 7       | Aceh Timur | Nurussalam  | Idi Fishing Port              | 258,93            | Hotspot         | 16,07               |

Table 5. Shows that the supply chain route with the lowest ACO cost is in Peudada District to the Peudada Fish Landing Base with a cost of 1.39 km, followed by Muara Batu with a cost of 2.26 km and Gandapura with a cost of 6.46 km. These results indicate that areas with low cost values have better

connectivity to the catchment points, making it more efficient to support the distribution of fishery products. Nurussalam District, which has hotspot status, is also included in the efficient route group with a cost of 16.07 km, so that the area not only has a significant concentration of production but also

still has quite good supply chain access. Conversely, several areas such as Seunuddon (72.45 km), Tanah Jambo Aye (71.37 km), Simpang Ulim (67.94 km), Lapang (55.91 km), Baktiya Barat (54.52 km) have higher costs, so attention is needed to improve accessibility and strengthen distribution

#### 4.4 Results of GIS-based Production, Hotspot, and Supply Route Map Integration

The integration stage of production maps, hotspots, and supply routes is carried out by displaying several main layers in the GIS system. The production layer is used to depict the distribution of Vannamee shrimp yields by sub-

channels. Thus, the results of ACO optimization show that supply chain development strategies need to consider not only the size of production, but also route efficiency and regional connectivity to the main collection points

district and regency, while the Getis-Ord Gi\* layer is used to show spatial status in the form of hotspots, coldspots, and insignificant areas. In addition, pond points, collection points, and distribution road networks are displayed as the basis for establishing supply chain routes, which are then optimized using ACO. The components of the GIS-based layer integration are Fig Figure 3., and Figure 4.

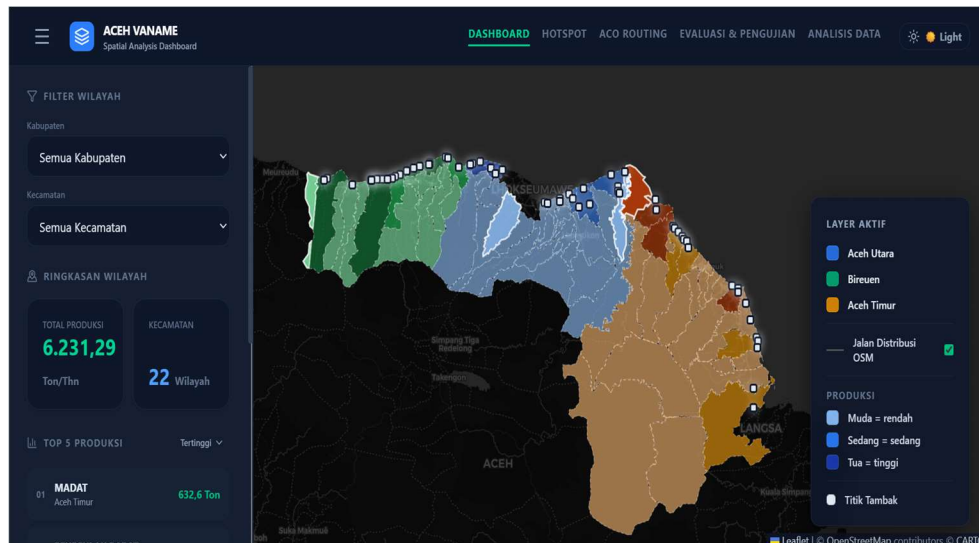


Figure 3: Integration of GIS-Based Fishery Pond Production and Location Maps

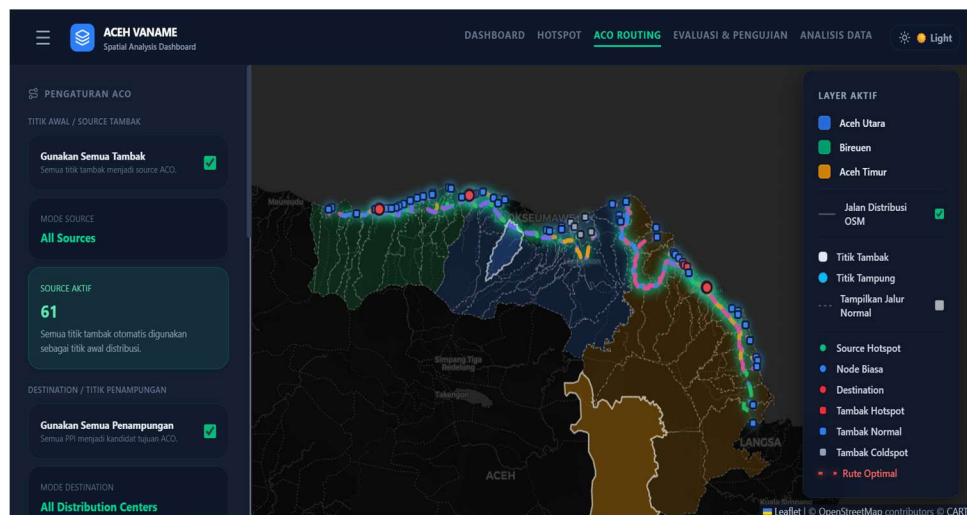


Figure 4: Supply Chain Integration ACO Optimization Results

#### 4.5 Visualization of Getis-Ord Gi\* Results Graph

The Getis-Ord Gi\* algorithm test results graph is used to display Vannamei Shrimp production patterns, GiZScore values, and hotspot and coldspot categories in the study area. Based on the

calculations, 22 sub-districts were analyzed, each with varying production values, GiZScore, and GiPValue. This graphic visualization helps identify sub-districts with high, low, or insignificant production concentrations spatially are in Figure 5.

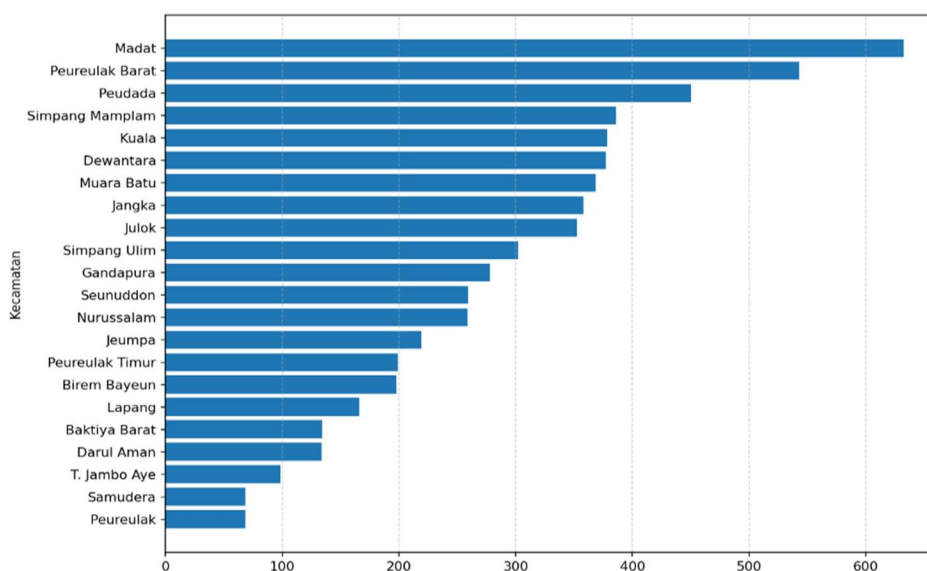


Figure 5: Distribution of Vannamei Shrimp Production by Sub-district

Based on Fig. 5, areas with high production should be considered as potential areas for developing Vannamei Shrimp cultivation. Areas with low production should be considered for land potential evaluation, infrastructure support, and

supply chain strengthening. Therefore, this production graph serves as a baseline for understanding fishery product distribution before conducting spatial analysis using Getis-Ord Gi\* are in Figure 6

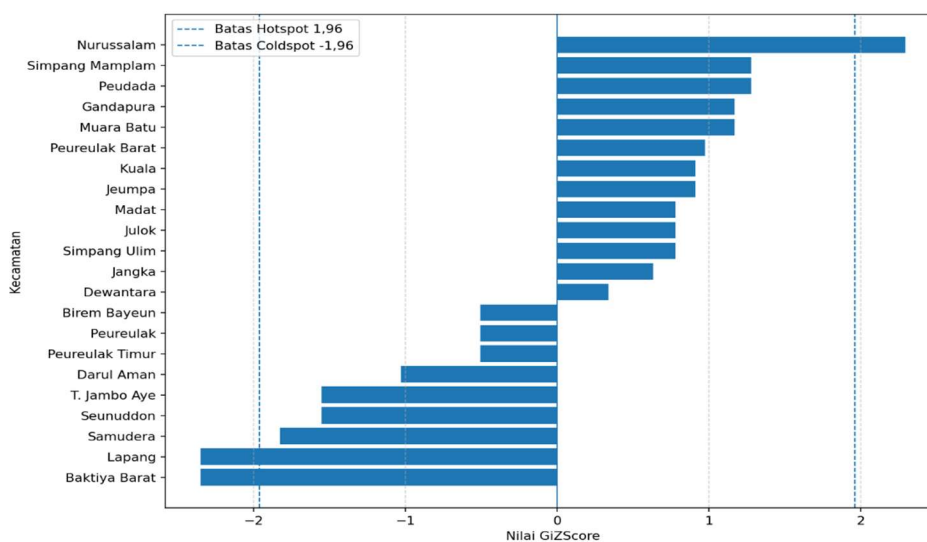


Figure 6: GiZScore Values Obtained from Getis-Ord Gi\* Analysis.

Figure 6, shows the spatial trend of each sub-district. A positive GiZScore indicates a region with a high production concentration, while a negative GiZScore indicates a region with a low production concentration. In this study, Nurussalam Sub-district had the highest GiZScore of 2.2946 with a p-value of 0.0218, categorizing it as a hotspot. This indicates that Nurussalam Sub-district has a significant spatial concentration of Vannamei Shrimp production. Lapang and Baktiya Barat Sub-districts had GiZScore values of -2.3479 with a p-value of 0.0189, categorizing them as coldspots. These negative values indicate that both sub-districts have a significantly low production concentration. The other sub-districts were categorized as not significant because their GiZScore and p-value did not meet the significance threshold for hotspots or coldspots. Thus, the GiZScore graph clarifies the spatial classification results obtained by the Getis-Ord Gi\* algorithm.

Figure 7, shows that of the 22 sub-districts analyzed, one district was categorized as a hotspot, two were categorized as cold spots, and 19 were categorized as insignificant. These results indicate that most of the study areas have not yet formed a significant spatial cluster pattern. However, the presence of Nurussalam Sub-district as a hotspot indicates the presence of a high production concentration that can be prioritized in planning the development of Vannamei Shrimp production and supply chains. The coldspot category in Lapang and Baktiya Barat Sub-districts indicates areas with low production concentrations that require attention in the development of the Vannamei Shrimp fishery sector.

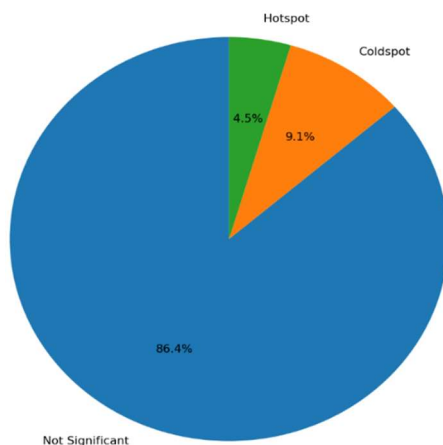


Figure 7: Classification of Hotspot, Coldspot, and Not Significant Areas Based on Getis-Ord Gi\*

#### 4.6 Ant Colony Optimization Algorithm Test Results Graph

Visualization of the Ant Colony Optimization algorithm test results is used to display the process and results of optimizing the vaname shrimp supply chain. The ACO graph is created based on the results of model evaluation, the distribution of collection destinations, node selection probabilities, ant route simulations, and pheromone updates. Figure 8., shows a decrease in distribution distance after the optimization process. Based on the model evaluation results, the normal distance is 1905.92 km, while the ACO optimized distance is 1905.60 km. The distance savings obtained is 0.32 km, with an efficiency level of 0.02%. Although the efficiency value obtained is relatively small, these results indicate that the ACO algorithm is capable of producing shorter distribution routes than the normal route. This proves that the ACO method can be applied in GIS-based modeling of the Vannamei shrimp supply chain. Small distance differences can be influenced by road network conditions, the distribution of pond locations, and the proximity of production points to existing collection points.

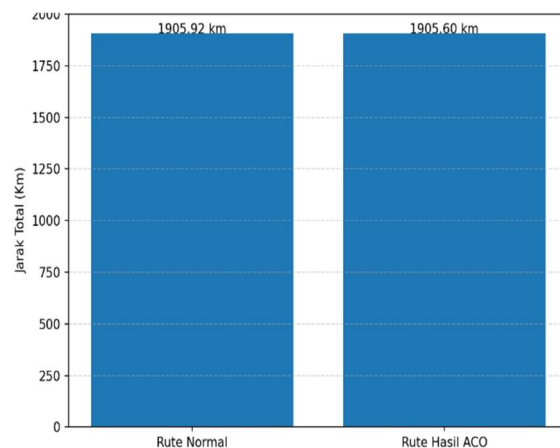


Figure 8: Comparison Between Initial Distribution Distance and Optimized Distance Generated by ACO.

Based on the calculation results, Peudada has the highest probability of 0.43010901 because it has the closest distance from the starting point A, which is 1.39 km. Muara Batu is in second place with a probability of 0.26453607, while Lapang has the lowest probability of 0.01069311 because it has the furthest distance from the starting point. This graph shows that in the ACO algorithm, distance has a

large influence on the visibility value and the probability of path selection. The closer the distance of a node, the higher its visibility value, so the chance of that node being selected is greater. Thus, this probability graph shows the initial process of ant

decision making in determining the path to be taken. Figure 9., shows the opportunity for each location to be selected by the ants in the initial process of the ACO algorithm.

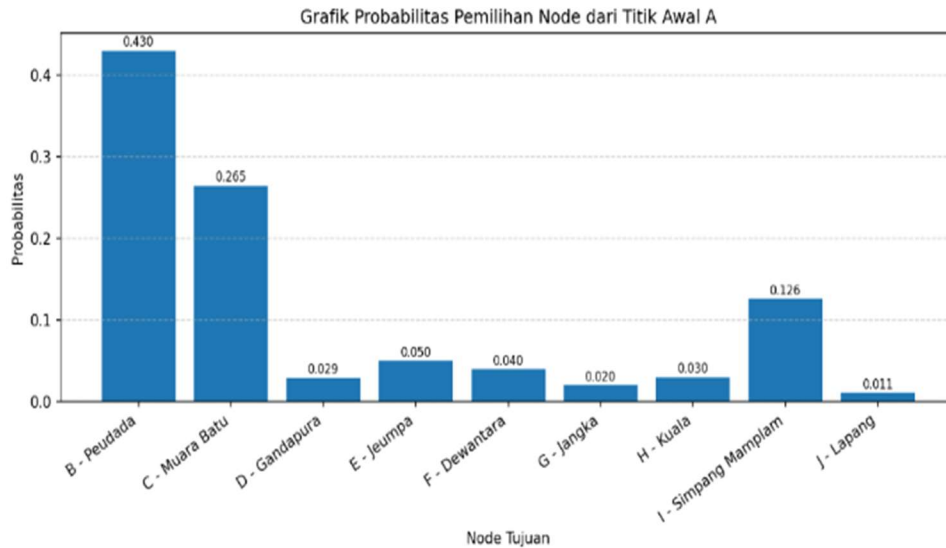


Figure 9: Probability of Node Selection from Initial Node A.

Fig. 10., shows the development of the distance traveled by the ants from the starting point until returning to the depot. The route formed is A to B, C, D, E, F, G, H, I, J, then back to A. The total distance of the closed route obtained is 111.82 km. This graph shows that the cumulative distance increases gradually with each node movement. A significant increase in distance is seen in the movement from I to J and from J back to A because the distance between these nodes is further than the previous movement. With this cumulative graph, the process of route formation by the ants can be understood more clearly and shows the part of the route that makes the largest contribution to the total distance. Cumulative Graph of Ant Route Distance in Cycle 1 in Figure 10.

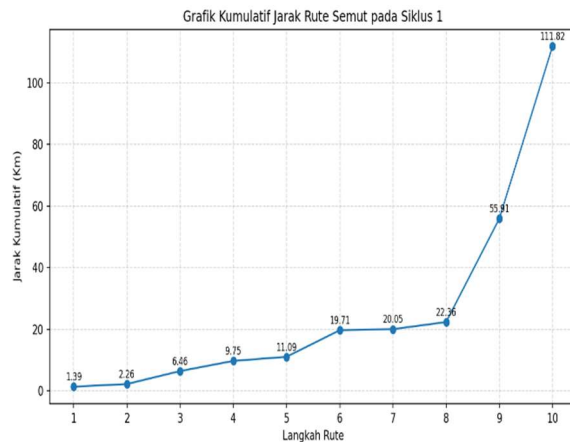


Figure 10: Cumulative Graph of Ant Route Distance in Cycle 1

Figure 11., shows a comparison between the initial pheromone value and the pheromone value after the update in the first cycle. The initial pheromone value of 0.01 increased to 0.01394294 after the route was traversed by the ants. This increase occurred due to the addition of pheromone based on the total distance traveled by the route. This result indicates that the path traversed by the ants will receive pheromone reinforcement, thus having a greater chance of being selected in the next cycle. In the ACO algorithm, pheromone updates are crucial because they function as collective memory in the optimal path search process. The better a route, the greater the chance of it being strengthened through pheromone addition. Graph of Pheromone Changes in Cycle 1 in Figure 11.

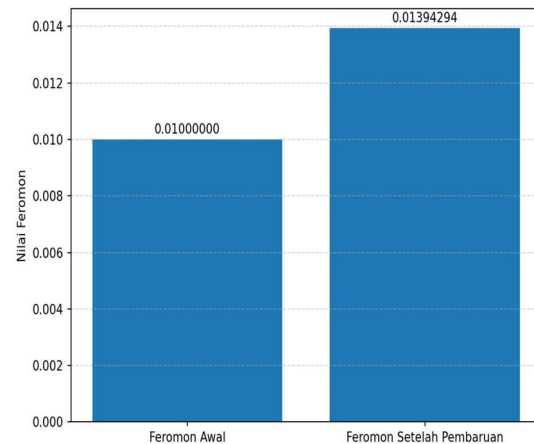


Figure 11: Graph of Pheromone Changes in Cycle 1

## 5. CONCLUSIONS

The results of spatial analysis using the Getis-Ord Gi\* method successfully identified the distribution pattern of Vannamei Shrimp fishery production in 22 sub-districts spread across Bireuen Regency, North Aceh Regency, and East Aceh Regency. Based on the results of the z-score and p-value calculations, one area was categorized as a hotspot, namely Nurussalam District with a GiZScore of 2.2946 and a GiPValue of 0.0218. In addition, there are two areas categorized as coldspots, namely Lapang and Baktiya Barat Districts with a GiZScore of -2.3479 and a GiPValue of 0.0189. A total of 19 other sub-districts are in the not significant category. These results indicate that the production pattern of Vannamei Shrimp fishery products in the study area is not only influenced by the amount of production value, but also by the spatial relationship between regions.

The results of supply chain optimization using the Ant Colony Optimization (ACO) Algorithm based on Geographic Information System (GIS) successfully produced a more efficient distribution route from fishery pond locations to collection points. The optimization process was carried out on 61 fishery pond points connected to three main collection points, namely Peudada Fishery Port, Krueng Mane Fishery Port, and Idi Fishery Port. The evaluation results showed that the total distribution distance could be optimized from 1905.92 km to 1905.60 km with a distance saving of 0.32 km or an efficiency of 0.02%. In addition, several areas such as Peudada, Muara Batu, and Gandapura have low distribution costs, while areas such as Seuneudon, Tanah Jambo Aye, Simpang Ulim, Lapang, and Baktiya Barat have higher costs and therefore

require attention in developing accessibility and distribution networks. Thus, the integration of the Getis-Ord Gi\* and ACO methods in a GIS system can support the identification of priority production areas and the optimization of the Vannamei Shrimp supply chain in the northern coastal region of Aceh, Indonesia.

Further research is recommended using production data over a longer time period and add other variables that influence the production and distribution of white shrimp so that the analysis results are more comprehensive. In addition, distribution route optimization can be developed by considering cost, travel time and road network conditions, as well as comparing the performance of the Ant Colony Optimization (ACO) algorithm with other optimization algorithms to obtain more optimal results.

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## REFERENCES:

- [1] Kementerian Kelautan dan Perikanan Republik Indonesia, *Kelautan dan Perikanan dalam Angka 2023*. Jakarta, Indonesia: KKP RI, 2023
- [2] A. Rasyidah, S. Sunaryo, E. Yudiati, and I. Widiasta, "Physico-Chemical Dynamics of Vanname Shrimp (*Litopenaeus vannamei*) Cultivation Pond Water Quality with A

- Recirculation System,” *Journal of Marine Biotechnology and Immunology*, vol. 2, no. 1, 2024. doi:10.61741/8pvwk765
- [3] Y. Nugroho, T. Athaillah, and M. Qadri, “Efficiency analysis of vannamei shrimp supply chain performance in PT Sari Indonesia Group, Suak Pandan Village, West Aceh Regency, Aceh Province,” *IOP Conference Series: Earth and Environmental Science*. 2022; 1041, doi:10.1088/1755-1315/1041/1/012005
- [4] A. Mustafa, M. Paena, A. Athirah, E. Ratnawati, R. Asaf, H. Suwoyo, S. Sahabuddin, E. Hendrajat, K. Kamaruddin, E. Septiningsih, A. Sahrijanna, I. Marzuki, and K. Nisaa, “Temporal and Spatial Analysis of Coastal Water Quality to Support Application of Vannamei Shrimp *Litopenaeus vannamei* Intensive Pond Technology,” *Sustainability*, vol. 14, no. 5, 2022, doi:10.3390/su14052659.
- [5] Y. Liu, X. Yang, Z. Wang, et al, “Mapping the fine spatial distribution of global offshore surface seawater mariculture using remote sensing big data,” *International Journal of Digital Earth*, vol. 17, 2024, doi:10.1080/17538947.2024.2402418
- [6] P. Yudhi, and R. Rakhmaati, “Supply Chain Management and Value Chain Governance Distribution Channel of Shrimp,” *International Journal of Innovations in Engineering Research and Technology*, vol. 8, no. 8, 2021, doi:10.17605/osf.io/da3hp.
- [7] N. Nurdin, M. Zarlis, T. Tulus, and S. Efendi, “Optimization and Computing Model of Fish Resource Supply Chain Distribution Network,” *IOP Conf. Series: Journal of Physics: Conf. Series*, 1898:012022, 2022.
- [8] R. Xiao, M. Xiao, H. Xia, and Z. Zhu, “Optimizing Port Seafood Logistics Paths: A Multi-Objective Approach for Zero-Carbon and Congestion Management,” *Sustainability*, vol. 17, no. 5, 2025, doi:10.3390/su17052311
- [9] S. Zhang, “Applications of Marine Geographic Information Systems (GIS) in Ocean Surveying,” *Advances in Computer, Signals and Systems*, vol.1, no. 1, 2024, doi:10.23977/acss.2023.071009
- [10] N. Nurdin, B. Bustami, R. Meiyanti, and A. Fahada, “Clustering Types of Capture Fisheries Products Using the K-Means Clustering Algorithm,” *Journal of Theoretical and Applied Information Technology* vol.102, no. 17, pp. 6482-6492, 2024
- [11] F. Suryana, N. Nurdin, and D. Hamdhana, “Implementation of Ant Colony Optimization (ACO) Algorithm for Route Optimization of Tourist Paths in Takengon,” *J Appl Informatics Comput.*, vol. 9, no. 4, pp. 1886–1896, 2025, doi:10.30871/jaic.v9i4.9706
- [12] M. A. Awadallah, S. Makhadmeh, M. Al-Betar, et al, “Multi-objective Ant Colony Optimization: Review,” *Archives of Computational Methods in Engineering*, vol. 32, pp. 995 – 1037, 2024, doi:10.1007/s11831-024-10178-4
- [13] Y. Liu, H. Zhang, Z. Gan Z, et al, “Pheromone-Focused Ant Colony Optimization algorithm for path planning,” *2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. 2025. doi:10.1109/smc58881.2025.11343528
- [14] N. Nurdin, B. Bustami, and M. Maryana, “Robust optimization approach for agricultural commodity supply chain planning,” *Journal of Theoretical and Applied Information Technology* vol. 99, no. 2, pp. 304–315, 2021.
- [15] C. Qi, “Multi-objective Optimization-Based Algorithm for Selecting the Optimal Path of Rural Multi-temperature Zone Cold Chain Dynamic Logistics Intermodal Transportation,” *International Journal of Computational Intelligence Systems*, vol. 17, 2024, doi:10.1007/s44196-024-00616-3
- [16] N. Nurdin, M. Zarlis, T. Tulus, and S. Efendi, “Mixed Integer Linear Programming Model for Integrated Fish Supply Chain Planning,” *Journal of Theoretical and Applied Information Technology*, vol. 98, no.12, pp. 2017-2028, 2020.
- [17] N. Nurdin, Fajriana, R. Meiyanti, Adelia, and M. Maulita, “Clustering and Mapping of Agricultural Production Based on Geographic Information System Using K-Medoids Algorithm”, *JATIT*, vol. 5, pp. 116–124, Feb. 2025, doi: 10.37965/jait.2025.633
- [18] A. Huang, J. Zhuang, Y. Ren, Y. Rao, and S. Tsai, “Supply Chain Management in the Digital Economy,” *Journal of Global Information Management*, vol. 32, no. 1, pp. 1-27, 2024, doi: 10.4018/jgim.361589.
- [19] O. Elufioye, C. Ike, O. Odeyemi, F. Usman, and N. Mhlongo, “AI-driven predictive analytics in agricultural supply chains: a review: assessing the benefits and challenges of ai in forecasting demand and optimizing supply in agriculture,” *Computer Science & IT Research Journal*, vol. 5, no. 2, pp. 473-497, 2024, doi: 10.51594/csitrj.v5i2.817.
- [20] J. Q. Li, C. H. Cheng, B. C. Choi, J. T. Kwon, and Y. M. Dai, “Dynamic risk-aware ant colony optimization for low-carbon routing in

- perishable food supply chains,” *Results Eng.*, vol. 30, no. December 2025, p. 109776, 2026, doi: 10.1016/j.rineng.2026.109776
- [21] M. Lahdhiri, M. Jmali, T. Hamdi, and A. Babay, “Applying Ant Colony Algorithm for Transport Optimization in Textile Industry Supply Chain,” *Autex Res. J.*, vol. 25, no. 1, 2025, doi: 10.1515/aut-2025-0058.
- [22] H. Wu, and Y. Gao, “An ant colony optimization based on local search for the vehicle routing problem with simultaneous pickup-delivery and time window,” *Appl. Soft Comput.*, vol. 139, 110203, 2023, doi:10.1016/j.asoc.2023.110203
- [23] Z. Wan, Y. Guo, J. Yang, X. Wang, and J. Li, “Logistics Routing Intelligence based on Improved Ant Colony Algorithm and Dijkstra Algorithm,” *Frontiers in Science and Engineering*, vol. 4, no. 8, 2024, doi: 10.54691/669kn656
- [24] H. Kim, and J. Park, “Spatial hotspot analysis using Getis-Ord  $G_i^*$ ,” *Journal of Spatial Analysis*, vol. 15, no. 3, pp. 211–223, 2021.
- [25] S. Mohamadi, M. Honarmand, S. Ghazanfari, and R. Hassanzadeh, “Hotspot and accumulated hotspot analysis for assessment of groundwater quality and pollution indices using GIS in the arid region of Iran,” *Environmental Science and Pollution Research*, vol. 30, pp. 69955–69976, 2023, doi:10.1007/s11356-023-27177-w
- [26] K. Akmal, “The Role of Geographic Information Systems (GIS) in Location-Based Decision Making,” *Journal Informatic, Education and Management (JIEM)*. Vol. 5, no. 1, 2023, doi:10.61992/jiem.v5i1.73
- [27] S. Chentouf, B. Sebbah, E. Bahousse, M. Wahbi, and M. Maâtouk, “GIS-Based Multi-Criteria Evaluation (MCE) Methods for Aquaculture Site Selection: A Systematic Review and Meta-Analysis,” *ISPRS Int. J. Geo Inf.*, vol. 12, no. 10, 439, 2023, doi:10.3390/ijgi12100439
- [28] M. Silverthorn, S. O. Yakubu, and L. Falconer, “Checklist and reporting framework to support documentation and communication of GIS-based Multi-Criteria Evaluation (MCE) models for aquaculture site selection,” *PLOS Sustainability and Transformation*. 2025, doi:10.1371/journal.pstr.0000155.
- [29] T. Luong, and T. Cao, “Use of Getis-Ord's statistic to detect hotspots and coldspots of COVID-19 in Hanoi City, Vietnam,” *World Journal of Biology Pharmacy and Health Sciences*, vol. 15, no. 3, pp. 102–109, 2023, doi:10.30574/wjbphs.2023.15.3.0394
- [30] X. Li, and Y. Zhao, “Optimization of transportation routing using ant colony algorithm,” *International Journal of Computational Intelligence*, vol. 7, no. 4, pp. 299–310, 2021.