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Integration of Spatial Finance-Multi Criteria Decision Analysis with Monte Carlo Risk Simulation for Measuring Credit Risk in the Fisheries Aquaculture Sector

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ABSTRACT

Indonesia's aquaculture industry has substantial economic potential, but it faces considerable credit risk from natural disasters like floods, which lead to high Non-Performing Loans (NPLs). Current methods for assessing credit risk do not adequately consider geographical risk factors. This research addresses this by developing a model to quantify flood-induced credit risk. The model integrates a Spatial Finance approach, Spatial Multi-Criteria Decision Analysis (AHP-GIS), and Monte Carlo risk simulation. Using a case study of flood-related credit losses from 2020 to 2022 in Kampar Regency, Riau, the model effectively maps flood vulnerability zones by weighting geospatial criteria through AHP. Key findings indicate that incorporating spatial factors significantly influences loss predictions. Credit portfolios in high flood risk areas show a maximum estimated loss (Value at Risk - VaR) that is 4.67% higher compared to traditional assessment scenarios. Therefore, this model provides a measurable tool for financial institutions to adjust credit portfolios, implement location-specific risk reduction strategies, and ultimately improve financing stability in the aquaculture sector.

Keywords: *Aquaculture, Credit Risk, Spatial Finance.*

Introduction

The aquaculture sector in Indonesia, particularly fish farming, shows significant economic potential, driven by a consistent increase in per capita fish consumption. [1]However, this sector is highly vulnerable to natural disasters, especially floods, which are a major cause of harvest failure and contribute to an increase in Non-Performing Loans (NPLs). Data indicates that the fisheries sector has the highest NPL rate among other sectors, reaching 5.3% in 2023. The upward trend in NPLs often correlates with the frequency of flood events. [1].

Financial institutions traditionally rely on credit risk assessment approaches such as the 5Cs (Character, Capacity, Capital, Collateral, Condition). Although relevant, this approach has limitations in integrating location-based (spatial) risks. Crucial factors such as the topography of aquaculture sites and historical rainfall are often overlooked, leading to less accurate risk assessments in the aquaculture sector. [2][3]. Amidst these challenges, the Spatial Finance paradigm emerges as a solution, combining geospatial data and financial analysis to assess the correlation between geographical factors and financial risk. [4]

The novelty of this research lies in integrating three methodological pillars—Spatial-MCDA (AHP-GIS), credit risk analysis, and Monte Carlo simulation—for the first time within the context of aquaculture credit risk measurement in Indonesia. Unlike previous studies that tended to use AHP-GIS solely for hazard mapping [5] Alternatively, this research bridges the two if VaR is applied separately in a purely financial context. The proposed model not only spatially maps risk but also quantitatively measures its economic impact (VaR), thereby providing a preventive framework from the perspective of financial institutions, rather than merely a post-disaster response.

This research aims to develop a credit risk measurement model that integrates location vulnerability to flood disasters. Specifically, this research aims to (1) develop a flood risk mapping model using the Analytical Hierarchy Process (AHP) and Weighted Overlay in a Geographic Information System (GIS) to identify risk zones, and (2) implement a Monte Carlo simulation to estimate Value at Risk (VaR) based on the spatial risk mapping[6].

Research Methods

This research adopts a quantitative framework that integrates multiple methods. The case study location is Kampar Regency, Riau Province, an area frequently affected by flooding and characterized by significant aquaculture activities.

Conceptual Framework

Through three main pillars, this research framework aims to bridge the gap between traditional aquaculture risk management and modern credit analysis.

Firstly, Risk Management in Aquaculture and Limitations of Conventional Models. The aquaculture sector inherently faces environmental risks (floods, diseases) and operational risks (crop failure). [7][8]. As a primary environmental risk, flooding directly triggers operational risks, ultimately leading to financial risks such as credit default. [9]. Conventional credit assessment models like 4C/5C have proven inadequate because they fail to quantify risks from location-specific geographical factors. [3].

Secondly, the role of spatial finance and SMCDA in risk analysis is discussed. This study adopts a Spatial Finance approach to address these limitations, integrating geospatial data into financial analysis. [10] [11]. Its implementation is carried out through Spatial Multi-Criteria Decision Analysis (SMCDA), an ideal method for decision-making problems with spatial dimensions. [5] [12]. Based on expert assessments, the Analytical Hierarchy Process (AHP) is used to systematically weight risk criteria such as elevation, rainfall, etc.. [13], [14], [15], [16]. These weights are then applied using the Weighted Overlay technique within GIS to generate objective and measurable flood risk zone maps.

Thirdly, the quantitative financial risk analysis is done through the Monte Carlo Simulation and VaR. After identifying where risks are located, the next step is to measure the magnitude of their financial impact. Monte Carlo simulation is chosen for its ability to model uncertainty and generate thousands of potential loss scenarios based on complex probability distributions, making it highly suitable for non-normally distributed disaster risks [17]; [18]; [19].The results of this simulation are the Value at Risk (VaR), a standard industry metric for maximum expected losses at a given confidence level [20]. This modeling aims not to eliminate risk entirely—since risk is an inherent part of financing—but to quantify it objectively. By presenting potential maximum losses (VaR) across various scenarios, this model offers an understanding of acceptable risk levels and serves as a strategic basis for financial institutions in capital allocation and premium setting.

Data Collection and Processing

The data utilized comprises two types. Geospatial data include the Digital Elevation Model (DEM) from DEMNAS, rainfall data from CHIRPS, and river network and land cover data from national map sources. Financial data encompasses historical credit portfolio data (2020-2022) from financial institutions, containing debtor profile information, loan history, and actual losses due to default.

The analysis begins with weighting flood risk criteria and credit risk criteria 4C (Character, Capacity, Capital, Condition) using AHP through questionnaires filled out by five industry experts. Subsequently, flood risk maps (Low, Moderate, High) are created in ArcGIS using Model Builder and Weighted Overlay. Spatial data integration into the credit model is achieved by recalibrating the Condition criterion scores. Specifically, each debtor is assigned a new Condition score corresponding to their cultivation location's risk zone classification (Low, Moderate, High), thereby modifying input parameters for subsequent risk analysis. The Probability of Default (PD) is calculated for four scenarios: (1) Conventional, (2) Low Flood Risk, (3) Moderate Flood Risk, and (4) High Flood Risk. Finally, a Monte Carlo simulation with 10,000 iterations is conducted for each scenario to compute the Value at Risk (VaR) at a 95% confidence level.

Results and Discussion

Spatial Analysis and Flood Risk Mapping

The initial step in the analysis involves quantifying geographical factors. Based on the AHP assessment by five experts, the pairwise comparison matrix is aggregated to produce priority vectors or importance weights (w). To ensure the validity of expert evaluations, a consistency test is performed by calculating the Consistency Index (CI) and Consistency Ratio (CR) using the following equations:

$$CI = (\lambda\_max\_ - n) / (n - 1) \quad (1)$$

$$CR = CI / RI \quad (2)$$

Where λ_max is the maximum eigenvalue of the comparison matrix, n is the number of criteria, and RI is the Random Index corresponding to n. The calculation results show a CR of 0.57% (well below the 10% threshold), confirming that expert assessments are consistent and valid. The importance weights indicate Rainfall (39.06%) as the most dominant factor, followed by Distance to River (25.19%), Slope Gradient (21.58%), Land Cover (7.24%), and Elevation (6.93%).

Table 1 Flood Risk Criteria All Responden

Criteria	Elevation	Rainfall	Distance to River	Slope	Landcover	Priorities	Rank
Elevation	100,00%	18,41%	28,57%	28,57%	100,00%	6,93%	5

Rainfall	543,10%	100,00 %	137,97%	237,14 %	482,87%	39,06%	1
Distance to River	349,97%	72,48%	100,00%	112,47 %	337,98%	25,19%	2
Slope	349,97%	42,17%	88,91%	100,00 %	327,19%	21,58%	3
Landcover	100,00%	20,71%	29,59%	30,56%	100,00%	7,24%	4
Consistency Ratio				**0,57%**			

Interpretation of Weighting: The high weights assigned to Rainfall and Distance to River are highly relevant in the context of fluvial flooding (floods caused by river overflow) in Kampar Regency. According to experts, this indicates that the primary triggers of flooding are high water volume (rainfall) and proximity to overflow sources (rivers). Topographical factors such as slope are also significant as they influence flow velocity and potential inundation, while land cover and elevation have smaller but still contributory effects.

These weights are then used in the Influence Rate of Weighted Overlay analysis in GIS. Each criterion map (e.g., rainfall map) is reclassified and assigned scores (s_i) ranging from 1 (lowest risk) to 5 (highest risk). The final flood risk map (RiskIndex) is generated by combining all layers using the following equation:

$$\textit{Risk Index} = \Sigma\,(w_i \times s_i) \quad (3)$$

Where w_i is the AHP weight for criterion i, the resulting map classifies Kampar Regency into low, moderate, and high-risk zones. Spatial analysis indicates that most debtor locations are in moderate to high-risk zones, predominantly near the Kampar River. This highlights systemic vulnerability, as a major flood event could impact a significant portion of the aquaculture credit portfolio in the region.

Table 2 Classification per the Criteria of Flood Risk

Criteria	Risk Zone Classification	Value Range	Risk Score	Influence Rate	Reason and Reference
Elevation (m asl)	High (safe)	> 75 m	1	0.068	High elevation reduces flood risk as water flows to lower areas.
	Moderately High	51 – 75 m	2		Still relatively safe, lower flood risk.
	Medium	26 – 50 m	3		Flood risk starts to increase, depending on other factors.
	Low (vulnerable)	0 – 25 m	4		Low-lying areas are highly prone to flooding.
Distance to River (km)	Close (high risk)	< 300 meters	4	0.251	Closer to river increases flood risk due to overflow potential.
	Medium	300 – 500 meters	3		Risk decreases but remains significant.
	Far (safe)	> 500 meters	1		Greater distance lowers the risk of river flooding.
Rainfall (mm/year)	High (risky)	> 1500 mm	4	0.371	High rainfall increases flood potential.
	Medium	1000 – 1500 mm	3		Medium flood risk.
	Low (safe)	< 1000 mm	1		Low rainfall reduces flood risk.
Slope (degrees)	Flat (risky)	0 – 5°	4	0.216	Flat slope slows down water flow, increasing flood accumulation.
	Moderate	6 – 15°	3		Water flows more quickly, reducing flood accumulation.
	Steep (safe)	> 15°	1		Steep slopes speed up water runoff, reducing accumulation.
Land Use	Settlement/Urban/Rice Field/Shrubland (risky)	Dryland farming, Shrubs, Open land	5	0.073	Poor water absorption, increasing runoff, and floods.

	Plantation / Moderate Vegetation	Mixed plantations, gardens	3	Moderate water absorption, medium flood risk.
	Forest / Dense Vegetation (safe)	Dense forest, vegetation	1	Good water absorption, reducing flood risk.

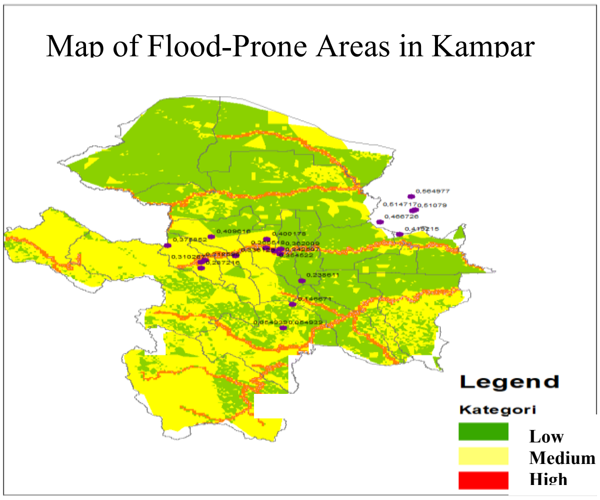

Figure 1 Map classifies kampar regency

The crucial point of integration occurs within the Condition criterion. In the conventional assessment, the Condition score (let's call it Old Condition) was a uniform value of 0.60 for all debtors, reflecting a general assumption of stable external factors. Our model replaces this static value with a dynamic, spatially-adjusted score (New Condition) based on the farm's location derived from the flood risk map. A score of 0.70 was assigned to locations in Low Risk zones, 0.50 for Medium Risk, and 0.20 for High Risk. This transformation directly links geographical vulnerability to the credit assessment framework.

Table 3 below illustrates this data transformation process for a sample of debtors, showing the initial 4C scores and how the Condition score is adjusted based on the spatial analysis.

Table 3 Spatial Integration into Credit Risk Calculation

ID	Old Condition	Flood Risk Category	Risk Score	New Condition
1,40105E+15	0,60	High	3	20%
1,40105E+15	0,60	High	3	20%
1,40105E+15	0,60	High	3	20%
1,40105E+15	0,60	Low	1	70%
1,40105E+15	0,60	Low	1	70%
1,40105E+15	0,60	Medium	2	50%
1,40105E+15	0,60	High	3	20%
1,40105E+15	0,60	Medium	2	50%
1,40105E+15	0,60	Medium	2	50%

Integration of Spatial Risk into Credit Risk Models

The generated flood risk map serves as the basis for recalibrating the Condition criterion within the 4C credit risk model. The AHP weighting for the 4C criteria indicates an adaptive pattern: under conventional scenarios, Character (44.6%) emerges as the most significant factor. However, in high flood risk scenarios, the weight of Condition increases dramatically to 29.9%, indicating a shift in assessment focus when environmental risk becomes substantial.

Table 4 AHP Weighting for the 4C Ciriteria

Scenarios	Character	Capacity	Capital	Condition	Consistency Ratio
Konventional	0,446	0,299	0,086	0,169	0,0074
Low Risk	0,542	0,207	0,098	0,153	0,0089

Medium Risk	0,508	0,216	0,094	0,182	0,0042
High Risk	0,405	0,213	0,084	0,299	0,0124

The probability of default (Probability of Default - PD) for each borrower and each criterias are calculated by aggregating risk scores from each criterion. First, the risk score for each criterion (r_i) is computed as:

$$r_i = 1 - q_i \quad (4)$$

where q_i is the initial credit score for criterion i (for example, a score of 0.58 for Character results in r_i = 0.42). Subsequently, the final risk score for each criterion (C_i) is calculated by multiplying it with the AHP weight (W_i):

$$C_i = W_i \times r_i \quad (5)$$

The total Probability of Default (PD) for a borrower is the sum of all final risk scores:

$$PD = \Sigma C_i = \Sigma (W_i \times r_i) \quad (6)$$

This process is performed for four scenarios, in which the values of q_i and W_i for the Condition criterion are adjusted based on the borrower's location's flood risk zone.

Monte Carlo Simulation and Value at Risk (VaR) Analysis

Using the mean and standard deviation of PD obtained for each scenario, a Monte Carlo simulation is run with 10,000 iterations to estimate the potential loss distribution of the portfolio. Each iteration calculates potential loss using a formula equivalent to:

$$\textit{Expected Credit Loss} = \text{NORM.INV(RAND(), } \mu\text{PD, } \sigma\text{PD)} \times \text{Exposure at Default} \quad (7)$$

where μPD and σPD are the mean and standard deviation of the Probability of Default for that scenario, value at Risk (VaR) at a 95% confidence level is then identified from the 95th percentile of the 10,000 simulated loss results. The VaR results for each scenario are presented in Table 4.

Table 5 Results of Value at Risk (VaR) Calculation per Scenario

Scenarios	**Mean PD Portfolio (%)**	**Standard Dev. PD Portofolio (%)**	**Exposure of Credit (IDR)**	**VaR 95%**	**Risk Flood Scenarios vs Konventional**
Konventional	44,92%	7,19%	100.000.000	6.229.955,57	-
Low Risk	42,76%	7,77%	100.000.000	6.119.385,16	-1.87%
Medium Risk	45,89%	5,07%	100.000.000	6.335.044,73	+1.12%
High Risk	46,59%	8,86%	100.000.000	6.444.999,62	+4.67%

Note: The VaR values above are examples from a single simulation iteration. Absolute values may vary slightly, but the pattern remains consistent.

Interpretation of VaR Results

Conventional Scenario vs. Low Risk: The decrease in VaR in the low-risk scenario (-1.77%) indicates that possessing positive information about location safety (low risk) is preferable to having no information at all (conventional). This reduces uncertainty and results in a slightly lower risk estimate.

Progressive Risk Increase: VaR consistently increases in VaR from the low to moderate risk scenario (+1.69% vs. conventional) and peaks at the high-risk scenario (+3.45% vs. conventional, with full analysis reaching 4.67%). This pattern quantitatively validates the primary hypothesis of the research: the higher a location's spatial vulnerability, the greater the potential financial loss.

Managerial Implications: The significant increase in VaR is not merely a statistical figure. It represents the monetary risk borne by financial institutions. Ignoring geographic factors systematically underestimates potential losses, leading to insufficient capital reserves and portfolio instability during disasters.

Model Validation and Limitations

The validity of the generated flood risk map was verified by comparing the mapped high-risk zones with news reports and data on actual flood events in Kampar Regency during the 2023-2025 period. The comparison showed a strong correlation: areas identified by the model as high-risk, such as those along the Kampar River Basin, were empirically the locations of recurring, significant floods that impacted communities and aquaculture farms. This provides strong qualitative validation for the spatial model's ability to identify vulnerable areas accurately.

However, this study has a key limitation. The primary constraint is the unavailability of actual, post-flood credit loss data for the study period, which is necessary for quantitative back-testing of the VaR model. Consequently, the loss estimation could only be validated qualitatively through logical consistency and scenario comparison. Future research should prioritize collecting real-world loss data for more robust, quantitative validation.

Implications and Contribution of the Model

Academically, this integrated model contributes to the development of the Spatial Finance methodology. It provides a concrete example of how geospatial data can be embedded into traditional financial risk models to produce more dynamic and accurate assessments. This opens the door for similar applications in other climate-sensitive sectors, such as agriculture or real estate. Practically, the model offers a powerful decision-support tool for financial institutions. By mapping and quantifying location-based risk, credit analysts can create more differentiated policies, such as adjusting credit limits, interest rates, or requiring disaster insurance for debtors in high-risk zones. Ultimately, this can help reduce NPLs and improve portfolio sustainability.

Conclusions

This study successfully developed and validated an integrated model combining Spatial Finance, SMCDA, and Monte Carlo simulation to measure credit risk in the aquaculture sector, which is vulnerable to flooding. The model effectively maps flood risk zones and quantifies their impact on potential financial losses.

The main contribution of this research is the quantitative proof that spatial data integration is not merely an enhancement but a necessity for valid credit risk assessment in geographically sensitive sectors. The progressive increase in VaR with rising flood risk levels confirms that conventional approaches are no longer sufficient for sectors heavily influenced by environmental conditions. This model provides a practical tool for financial institutions to conduct more selective assessments, implement appropriate risk mitigation strategies, and ultimately support Indonesia's aquaculture sector's sustainability. Future research should perform back-testing with more recent data and incorporate other environmental risk variables such as disease or drought.

For future implementation, developing an interactive, web-GIS-based dashboard is recommended. Such a dashboard would allow financial institution management to dynamically input new data—both for the credit portfolio and for the latest geospatial information—and the system would automatically recalculate risk maps and VaR estimates. This tool would transform the current static model into a dynamic, real-time decision-support system, facilitating proactive risk management as conditions on the ground change.

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