九州大学学術情報リポジトリ
Kyushu University Institutional Repository

Integrated Modeling and Spatial Analysis of Rice Production Waste Streams for Sustainable Resource Management in Agusan del Norte, Philippines

Michelle V. Japitana
Department of Geodetic Engineering, College of Engineering and Geosciences, Caraga State University

Darlyn B. Chatto
Department of Geodetic Engineering, College of Engineering and Geosciences, Caraga State University

Remle Nyl F. Ondoy
Department of Geodetic Engineering, College of Engineering and Geosciences, Caraga State University

Lorie Cris S. Asube
Department of Geodetic Engineering, College of Engineering and Geosciences, Caraga State University

https://hdl.handle.net/2324/7395592

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.716-723, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：
権利関係：Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International

KYUSHU UNIVERSITY

Integrated Modeling and Spatial Analysis of Rice Production Waste Streams for Sustainable Resource Management in Agusan del Norte, Philippines

Michelle V. Japitana[1,2], Darlyn B. Chatto[1], Remle Nyl F. Ondoy[1], Lorie Cris S. Asube[1,2]
[1]Department of Geodetic Engineering, College of Engineering and Geosciences, Caraga State University, Butuan City
[2]Caraga Center for Geo-informatics, Caraga State University, Butuan City
Corresponding Author e-mail: mvjapitana@carsu.edu.ph

Abstract: *Rice production in Agusan del Norte is critical for food security but generates substantial waste streams with potential environmental impacts. This study analyzes pesticide and fertilizer runoff in major rice-growing areas using satellite imagery, Geographic Information Systems (GIS), and field surveys. The study identifies critical risk zones by overlaying geospatial data with thematic layers, such as elevation, slope, soil drainage, and proximity to irrigation channels. Results show that poorly drained soil and low-lying areas near irrigation channels are prone to waste accumulation, leading to water contamination and soil degradation. Agricultural input usage varies: Butuan City relies on chemical inputs, Cabadbaran City uses minimal synthetic inputs, and Remedios T. Romualdez applies balanced methods. Proposed solutions include riparian buffer zones, improved drainage systems, and integrated pest management to reduce environmental impact. The study highlights the role of geospatial analytics in enhancing agricultural waste management and fostering sustainability in rice production.*

Keywords: geospatial mapping, rice production waste, risk assessment, pesticide run off, GIS.

1. INTRODUCTION

Rice production is a dominant agricultural activity in Agusan del Norte, Philippines significantly contributing to the province's economy and food security [1]. The province is a significant area for rice production with massive tracts of land dedicated to this vital crop. However, intensive rice cultivation generates substantial waste at various stages of production [2] including rice straw, husks, and other by-products [3] and plastics derived from farming practices.

A prior Focus Group Discussion (FGD) conducted with rice farmers within the Caraga State University campus is the motivation of this study. The FGD highlighted key rice farming practices in the aspect of waste management and input use. Despite the emergence of organic methods and modern technology, traditional farming using synthetic inputs remains prevalent among the respondents. Results gathered from the FGD suggest that while rice husks decompose naturally under modern harvesting, mechanized farming produces more inorganic waste, posing environmental challenges. The absence of comprehensive geospatial data portraying the extent of waste generation and where the waste streams (or natural pathways) limits effective waste management, leading to poor or limited mitigation planning and policy formulation, water contamination, and soil depletion. Hence, addressing these gaps through geospatial modeling and assessment at a local level is crucial.

Field survey data integrated with geospatial technologies like Remote Sensing (RS) and Geographic Information Systems (GIS) provides opportunities to characterize the extent of waste generation through map models [4],[5] while geospatial analyses of these maps can then be used to assess the potential risks of pollution in an area. Geospatial technology is dominantly used in identifying contamination hotspots, enabling targeted interventions for land use management and sustainable practices.

Thus, this study aims to map the rice production waste stream and assess the risk of pesticides and fertilizer runoff across the major rice-yielding areas of Agusan Province. Additionally, this study recognizes that the increasing challenge of chemical waste and intensive farming input requires attention. By combining local practices with advanced geospatial insights, this research promotes a balanced approach to improving productivity while ensuring environmental protection.

2. METHODOLOGY

2.1 The Study Area

This study focuses on Agusan del Norte's major rice-yielding areas, as shown in Fig. 1. According to the Philippine Rice Information System (PRISM) data for 2023, the leading rice-yielding regions of the province are Butuan City, Cabadbaran City, and Municipality of Remedios T. Romualdez. The land area of Agusan del Norte is over 354,686 hectares, and 25.43% of this is allocated for agriculture. Crops on these agricultural lands include rice, corn, coconut, banana, and mango [1],[4].

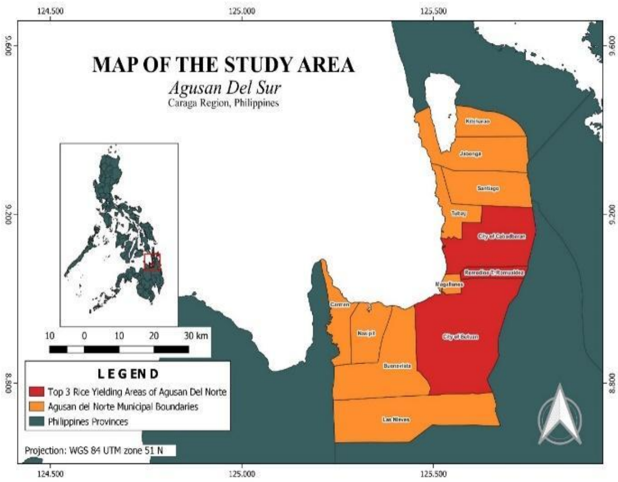

Fig. 1. The Map of the Study Area

2.2 The Methodological Flow

The flowchart for the entire process of this study is shown in Fig. 2. It outlines three major stages: data collection, processing and analysis, and mapping techniques and visualization.

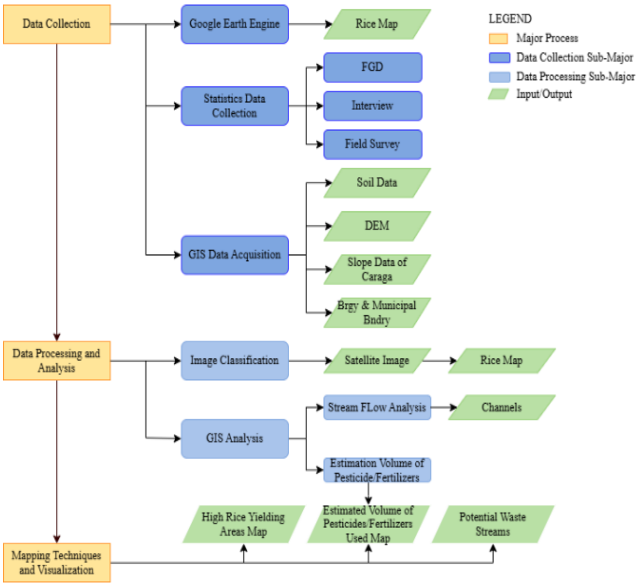

Fig. 2. The Procedural Flow of the Study

2.3. Data Gathering

2.3.1 Google Earth Engine and Image Classification

The study utilizes Google Earth Engine® (GEE) to acquire and analyze satellite imagery, offering extensive geospatial datasets and computational tools for environmental monitoring. Sentinel-1 Synthetic Aperture Radar (SAR) GRD data from the European Space Agency (ESA) were processed via custom scripts, providing high-resolution (10–40m) dual-polarization C-band SAR imagery, effective in all weather conditions. Preprocessing included thermal noise removal, radiometric calibration, and terrain correction. GEE also facilitated rice classification mapping through a custom model leveraging spectral and temporal satellite imagery. Training points from high-density rice-producing areas optimized classification accuracy, verified using Sentinel-1 SAR before classifier input. Post-classification processes [6] include noise reduction and accuracy assessment via confusion matrices and ground truth data. Standard accuracy metrics—Overall Accuracy, User's Accuracy, Producer's Accuracy, and the Kappa Coefficient ensure geospatial techniques' reliability, as shown in Table 1. Generated maps were cross-referenced with provincial rice production maps, validating classification against ground-truth data and enhancing the study's environmental and agricultural analysis credibility.

2.3.2. Statistics Data Collection

The researcher conducted FGDs with local farmers at Caraga State University-Main Campus to gather insights on agricultural waste generation and management. Structured questionnaires ensured unbiased data collection, covering waste types, disposal methods, pesticide and fertilizer use, and farming challenges. Pilot testing refined the questionnaire, while stratified sampling ensured representation across farm sizes and locations. Agricultural statistics from local agencies, including the Department of Agriculture (DA) and the Philippine Rice Research Institute (PhilRice), provided historical data on rice production. Field surveys validated satellite data and gathered primary information on farming practices, waste management, and stakeholder perspectives.

Table 1. Accuracy Metrics for Rice Classification Model: Overall Accuracy, Producer's Accuracy, Kappa Coefficient [7],[8].

Metric	Description	Standard Accuracy Range
Overall Accuracy	The percentage of correctly classified samples out of the total samples.	≥ 85%
User's Accuracy	The probability that a classified pixel represents that category on the ground (precision).	≥ 90%
Producer's Accuracy	The probability that a reference sample is correctly classified (recall).	≥ 80%
Kappa Coefficient	Measures agreement between classification and ground truth, adjusting for chance agreement.	≥ 0.75 (strong agreement), 0.4–0.75 (moderate agreement).
Confusion Matrix	A matrix showing true positives, true negatives, false positives, and false negatives for each class.	It should reflect minimal misclassification in key categories.

2.3.3. GIS Data Acquisition

The study utilizes Geographic Information Systems (GIS) for spatial analysis and mapping of rice waste streams. Boundary datasets, including municipal and barangay limits [9], were sourced from local agencies to define Agusan del Norte's top rice-producing areas. Digital Elevation Model (DEM) data were extracted using QGIS and the SRTM plugin, with preprocessing steps ensuring compatibility and accuracy. Topographic data on elevation and slope, obtained from the Department of Environment and Natural Resources (DENR), helps assess terrain influence on waste generation. Soil characteristics, including type and drainage, were also analyzed to understand nutrient retention and movement in rice production areas.

2.4. Data Processing and GIS Analysis

2.4.1. Rice Map

To ensure accuracy, the GeoTIFF rice map was loaded into QGIS for visualization [10] and clipped to Agusan del Norte's boundaries using the "Clip Raster by Extent" tool. Non-rice areas were excluded by assigning a NODATA value [11] value. The cleaned rice map was then converted to vector format [12] for advanced spatial analysis. Validation against a reference rice map from the Office of the Provincial Agriculturist used the "Select by Location" tool, applying geometric predicates to confirm spatial alignment. Misclassified areas were removed, ensuring a precise dataset for analyzing rice production waste streams and environmental impacts.

2.4.2. Stream Flow Analysis

Another analysis employed in this study is the watershed analysis to determine the water movement across the landscape and help identify areas where significant runoff of rice wastes occurs [13]. DEM data from the SRTM plugin was processed in QGIS using the SAGA plugin for streamflow analysis. Preprocessing removed depressions to ensure continuous flow, followed by stream network generation using the Strahler Order tool [14] to classify drainage patterns. Flow accumulation mapping pinpointed areas is prone to significant runoff, aiding in sustainable waste management and pollution reduction.

2.4.3. Estimating the Volume of Pesticides and Fertilizers Used

The study utilized geospatial analyses in QGIS to estimate pesticide and fertilizer usage in rice cultivation areas. First, rice fields were extracted using the "Clip" tool, aligning them with municipal boundaries for precision. A similar clipping procedure was applied at the barangay level in Butuan City (BXU), Remedios T. Romualdez (RTR), and Cabadbaran (CBR) to assess community-level agricultural practices. The "Field Calculator" converted area measurements to hectares by applying the expression sum($area/10000), converting the area measurements from square meters to hectares. The barangay boundary data was integrated with rice cultivation areas using the "Union" and "Dissolve" tools. Based on farmers ' Application Ratio (AR), a formula was then developed to determine the volume of pesticides and fertilizers per barangay.

$$AP = \frac{AR_1 + AR_2 + \ldots + AR_n}{n} \qquad \text{Equation 1}$$

As shown in Equation 1, the formula calculates the Average Pesticide (AP) and fertilizer application ratios by summing individual ratios and dividing by the total number of farmers. The data was transferred to an Excel file, imported as a CSV into QGIS, and processed with the "Field Calculator" to estimate input usage per rice area. This approach provided insights into application intensity, supporting agricultural policy development and sustainable management practices.

2.4.4. Potential Waste Stream Mapping

Mapping waste streams involves classifying environmental parameters elevation, slope, channels, soil texture, and soil drainage into four risk levels: Very High (4), High (3), Moderate (2), and Low (1). Lower elevations and flatter slopes are categorized as high-risk, while higher elevations and steeper slopes pose lower risks. Soil drainage and texture classifications are based on Agusan Survey Reports, with clay soil, which retains moisture, marked as very high risk. These classifications help identify areas vulnerable to waste accumulation and contamination, as shown in Table 2.

Geospatial datasets for Caraga, including elevation, slope, channels, soil texture, and drainage, were clipped to the study area to refine analysis. Using QGIS's "Select by Attributes" tool, risk levels were assigned based on specific value ranges. For example, slopes between 0–8% were classified as "Very High Risk" (4), while steeper slopes were assigned lower risk scores (1–3). A new field for risk level for Slope (P_S), was created in the Field Calculator, and values were applied accordingly. Similar classifications were made for elevation (P_E), channels (P_C), soil texture (P_{ST}), and soil drainage (P_{SD}).

$$Risk\ Level = (P_S * 0.2) + (P_{ST} * 0.2) + (P_{SD} * 0.2) + (P_E * 0.2) + (P_C * 0.2) \qquad \text{Equation 2}$$

The classified datasets were integrated using the Union tool, sequentially merging of layers were then implemented with slope, elevation, and channel data. A final risk assessment layer, Risk Streams, was created with a weighted formula shown in Equation 2 applied in the Field Calculator. Equation 2 balances the influence of terrain and soil properties on waste stream formation, reflecting their environmental impact due to the absence of established weight assignments in agricultural waste studies.

Table 2. Parameters used in Identifying Waste Stream Risks

Parameters (P)	Risk Levels			
	4	3	2	1
slope (S)	0-8%	8%-30%	30-50%	Above 50%
Soil Texture (ST)	Clay	Clay loam, Sandy clay loam, Silty Clay Loam	Loam, Sandy Loam, Silty Loam	Sandy, Stony, Rock Land, Mountain Soil
Soil Drainage (SD)	Very poorly drained	Poorly Drained	Moderately Drained	Well drained
elevation (E)	0-200	201-500	501-1000	Above 1000
channels (C)	Within the Channel			Not within the channel

In Table 3, the classified risk scores from QGIS Jenks Natural Breaks were categorized into predefined risk levels using the "Select by Attributes" tool, producing a final risk map showing Very High, High, Moderate, and Low-Risk areas. This process ensures accurate spatial representation of waste distribution. The Jenks Natural Breaks method was chosen for its ability to identify natural groupings within unevenly distributed data, such as rice waste generation at the farm level. It optimizes class breaks to group similar values while highlighting differences, ensuring the resulting classifications align with the data's patterns.

Table 3. Risk Ranges in Each Risk Class

Risk Numerical Value	Risk Classes
3.5 – 4	Very High Risk
2.9 – 3.4	High Risk
2.1 – 2.8	Moderate Risk
0 - 2	Low Risk

Fig. 3 illustrates the risk map development, starting with identifying environmental factors, classifying risk levels, and clipping datasets to the study boundary. Weighted calculations are applied using the Field Calculator and integrated with the Union tool. The overall risk score is computed, culminating in the final risk map visualization for assessing waste accumulation and environmental impact.

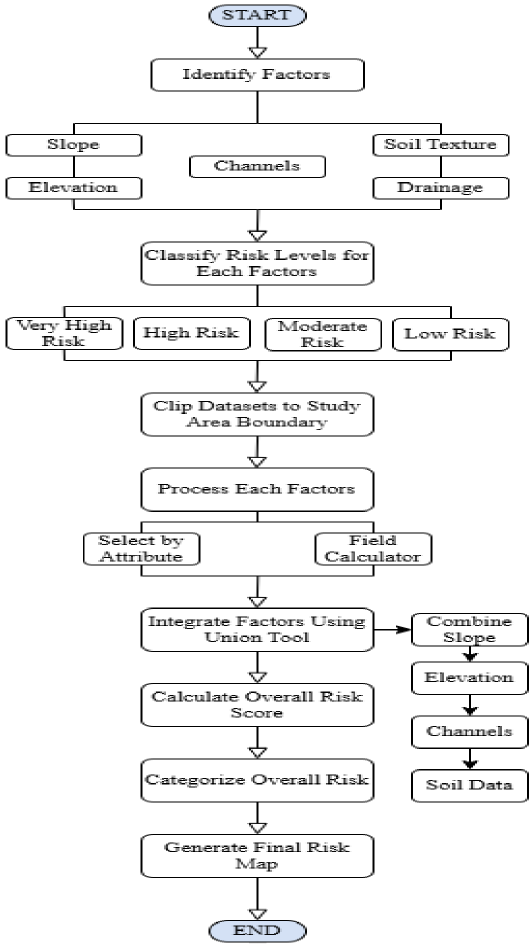

Fig. 3. Flowchart for Pesticides and Fertilizers Application Risk Zones

2.5. Mapping Techniques and Visualization

Waste stream maps overlay topography, soil type, and irrigation networks to highlight agricultural waste hotspots, emphasizing areas with poor drainage. Risk maps for pesticides and fertilizers integrate slope, proximity to water bodies, soil drainage, and land use, using gradient colors to indicate contamination levels. QGIS and GEE enhance visualization with interactive features, enabling precise analysis and informed decision-making.

3. RESULTS AND DISCUSSION

3.1. Rice Production Mapping and Classification

In Fig. 4, the study utilized Sentinel-1 SAR data processed through GEE to classify and map rice production areas in Butuan City, Cabadbaran City, and Remedios T. Romualdez. With an overall accuracy of 98.87% and a kappa coefficient 0.96, the classification strongly correlated with ground truth observations, validating the methodology. The rice maps highlighted clusters of rice fields concentrated in low-lying areas with favorable cultivation conditions, aligning with local agricultural reports. Despite high accuracy, minor misclassifications occurred in smaller croplands, likely due to limited training datasets. Expanding the dataset with diverse field samples could improve future classifications.

Results of the analysis showed that Butuan City has the highest rice-producing area with 4,903.202 hectares, followed by Remedios T. Romualdez with 1,146.932 hectares, and Cabadbaran City with 603.592 hectares. These findings highlight the study's precision in mapping high-yielding zones, offering valuable insights for targeted agricultural interventions and sustainable waste management strategies.

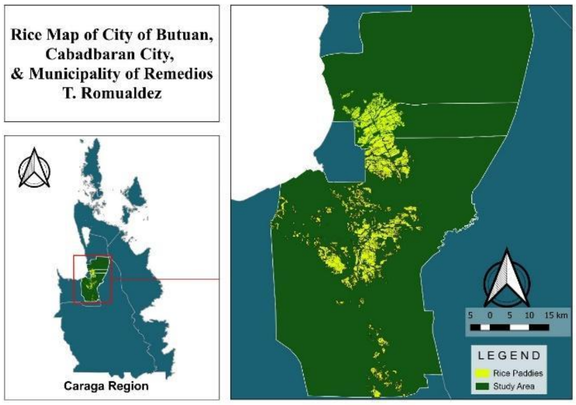

Fig. 4. Rice Production Map Based on Satellite Imagery

Table 4 presents the validation results of the classification method employed in mapping rice production areas using Google Earth Engine. The producer's accuracy of 97% confirms minimal omission errors, while the user's accuracy exceeds 96%, ensuring correct identification of rice fields. Training accuracy reached 98.87%, with minor misclassifications primarily in areas where spectral signatures overlapped. The validation accuracy was nearly identical at 98.88%, demonstrating strong generalization to unseen data. The kappa coefficient of 0.96 signifies a near-perfect agreement between classification results and ground truth data, reinforcing the reliability of the classification.The methodology proved effective in identifying rice paddies in the study area. It implies the scalability of these mapping techniques, which can be applied in other rice-producing regions to optimize agricultural monitoring and resource allocation. These methods are particularly relevant for areas with similar reliance on irrigation networks and flat terrains, offering a reliable tool for policymakers and researchers.

Table 4. Performance Metrics of the Classification Method

Classes	PA	UA	TA	VA	Kappa Coefficient
Rice	0.9701	0.9835			
Water	0.9274	0.9602			
Others	0.9951	0.9908			
Overall			98.87	98.88	96.77

Legend: Producer's Accuracy (PA), User's Accuracy (UA), Training Accuracy (TA), Validation Accuracy (VA)

3.2. Estimated Volume of Pesticides Used

Figs. 5 to 10 show the spatial patterns of pesticide usage, showing distinct patterns among Butuan City (BXU), Cabadbaran City (CBR), and Remedios T. Romualdez (RTR). Butuan City exhibited the highest herbicide utilization, ranging from 503–831 liters (L), facilitated by its flat terrain and irrigation networks. In contrast, CBR demonstrated moderate herbicide usage ranging from 240 to 312L, balancing chemical and manual weed control. RTR recorded lower herbicide application ranging from 274 to 303L, favoring alternative weed management strategies. The primary brands of herbicides used contain Benzobicyclon and Glyphosate, which pose moderate toxicity risks.

Insecticide application varied significantly, with RTR exhibiting the highest usage at 384–424L due to pest pressures, while CBR applied 196–255L in targeted areas. Butuan City exclusively used herbicides and practiced organic farming, avoiding insecticides and molluscicides. The main insecticides dominantly used in the area contain Lambda-cyhalothrin and Chlorpyriphos, classified as moderately toxic. Fungicide usage was observed only in RTR, targeting fungal diseases. These findings underscore the varying agricultural practices and chemical dependencies across municipalities, influencing environmental and economic outcomes.

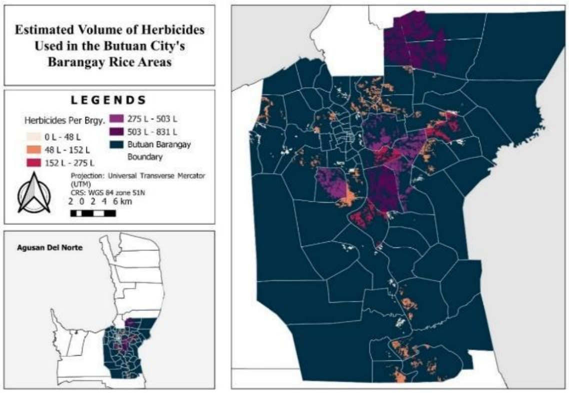

Fig. 5. Estimated Volume of Herbicides Used in Butuan City

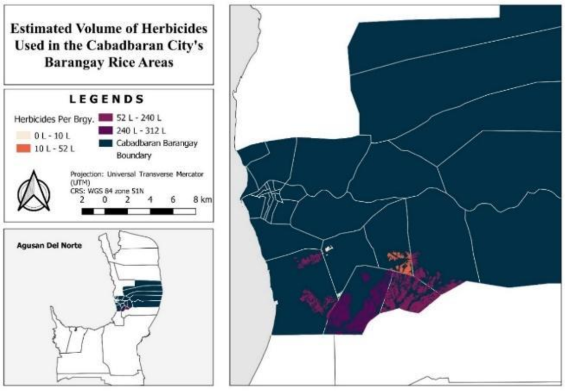

Fig. 6. Estimated Volume of Herbicides Used in Cabadbaran City

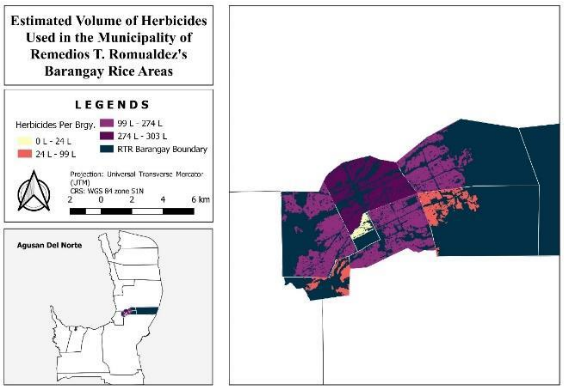

Fig. 7. Estimated Volume of Herbicides Used in RTR

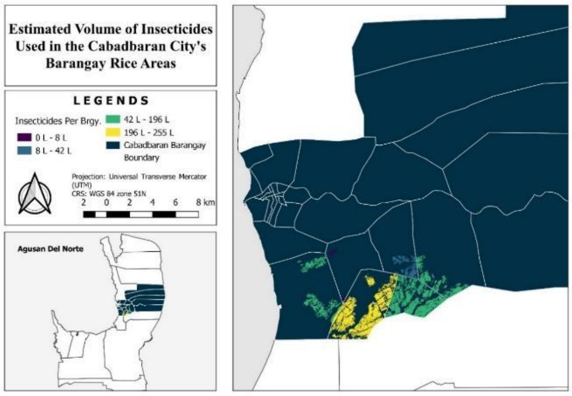

Fig. 8. Estimated Volume of Insecticides Used in Cabadbaran City

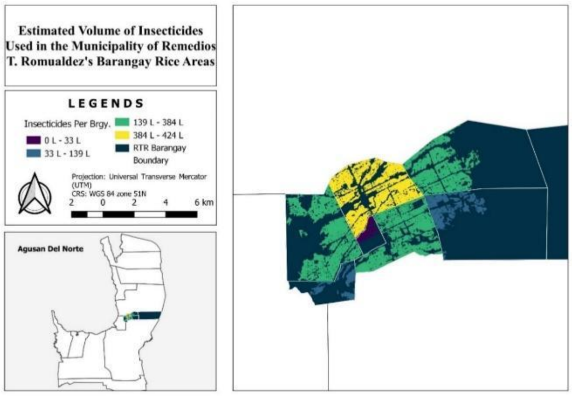

Fig. 9. Estimated Volume of Insecticides Used in RTR

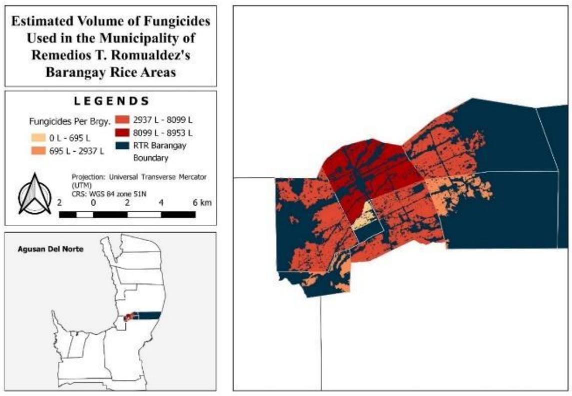

Fig. 10. Estimated Volume of Fungicides Used in RTR

In Figs. 11 to 13, the distribution of pesticide usage across Butuan City, Cabadbaran City, and Remedios T. Romualdez reveals significant differences in application levels. In Butuan City, Barangay Tagabaca recorded the highest herbicide usage at 800–900L, followed by San Vicente at 700–800L, reflecting intensive farming practices. In Cabadbaran City, herbicide application was lower, with barangay Sanghan leading at 300 L/ha, while Antonio Luna and La Union reported 200–250 L/ha and 100 L/ha, respectively. Insecticide usage followed a similar trend, with Sanghan applying 250 L/ha, indicating more balanced chemical use. These figures suggest Cabadbaran employs relatively sustainable farming methods compared to Butuan City's high herbicide dependency. Educational initiatives could enhance optimized pesticide use without compromising productivity.

Remedios T. Romualdez exhibited the highest pesticide usage among the three areas. Barangay Basilisa led in chemical applications, recording 300 L/ha of herbicides, 400 L/ha of insecticides, and 8,900 L/ha of fungicides, highlighting intensive agricultural activity. Lower pesticide volumes were found in Poblacion I and San Antonio, ranging from 20–30 L/ha of herbicides. The substantial chemical reliance in Basilisa raises concerns about runoff risks, particularly in areas with extensive irrigation networks and poorly drained soils. Implementing improved drainage systems and integrated pest management strategies could mitigate environmental impacts.

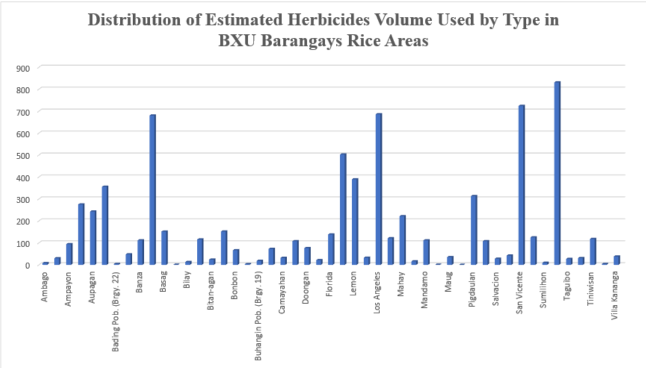

Fig. 11. Distribution of Estimated Volume of Herbicides Used in Butuan City

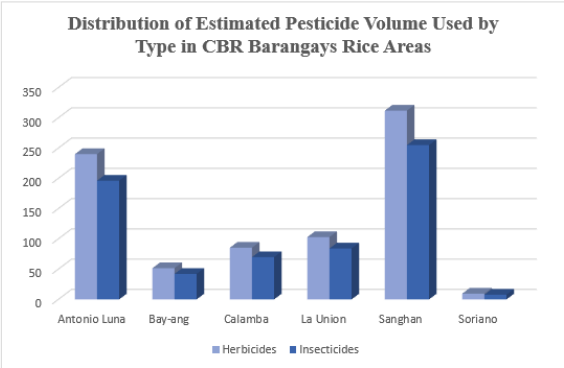

Fig. 12. Distribution of Estimated Volume of Pesticides Used in Cabadbaran City

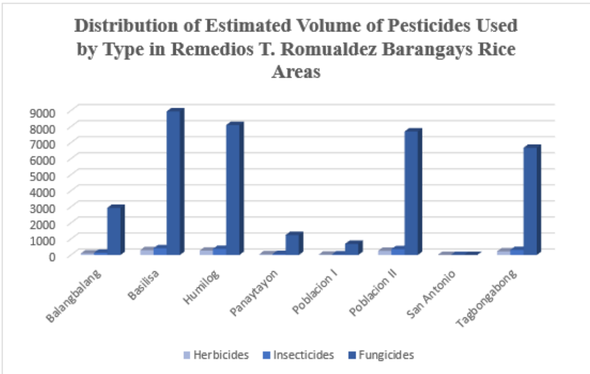

Fig. 13. Distribution of Estimated Volume of Pesticides Used in Remedios T. Romualdez

3.3. Estimated Volume of Fertilizers Used

The analysis of fertilizer usage across BXU, RTR, and CBR revealed significant variations influenced by locale farming intensity and nutrient management strategies. Butuan City exhibited the highest fertilizer application due to its extensive rice fields, while Remedios T. Romualdez applied fertilizers at moderate levels. Cabadbaran City's lowest overall fertilizer usage reflects its smaller scale, less chemically intensive farming practices.

Among fertilizers, 16-20-0 was intensively applied in Butuan City, ranging from 16,752 to 27,694 kg, while Cabadbaran reported moderate usage at 9,038 to 11,746 kg, with no application in Remedios T. Romualdez. Ammonium use peaked in Remedios T. Romualdez (28,144 to 31,109 kg), followed by Butuan City (15,077 to 24,925 kg), and least in Cabadbaran City (<11,490 kg). While Ammosol and Zinc Sulfate were exclusively applied in Remedios T. Romualdez, while Nitrogen supplements and plant growth stimulants were only used in Butuan City.

Complete fertilizer (16-16-16) showed extensive application in Remedios T. Romualdez (49,571 to 54,793 kg), moderate in Butuan City (20,102 to 33,233 kg), and minimal in Cabadbaran City (<19,331 kg). Urea, the most widely used nitrogen source, peaked in Remedios T. Romualdez (48,327 to 53,419 kg), followed by Butuan City (16,752 to 27,694 kg), and least in Cabadbaran City (<15,987 kg). Potash was most heavily applied in Butuan City (13,960 to 23,079 kg), with moderate usage in Remedios T. Romualdez (7,676 to 8,484 kg) and minimal in Cabadbaran City (<5,873 kg).

These findings highlight the varying agricultural practices, with Butuan City employing intensive chemical inputs, Remedios T. Romualdez balancing productivity with environmental considerations, and Cabadbaran City maintaining lower fertilizer dependency. Understanding these usage patterns supports targeted interventions for sustainable farming and improved nutrient management strategies.

Fig. 14 highlights Butuan City as the highest fertilizer user, with Complete NPK fertilizer, Ammonium Phosphate, and Urea reaching 294,000 kg, 245,000 kg, and 245,000 kg, respectively. Remedios T. Romualdez is the second highest user of Complete NPK fertilizer with 220,000 kg, while Cabadbaran City records moderate usage at 50,000 kg only. These patterns underscore the need to reduce chemical reliance of Butuan City in their rice farming and promote sustainable practices for optimized pesticide management.

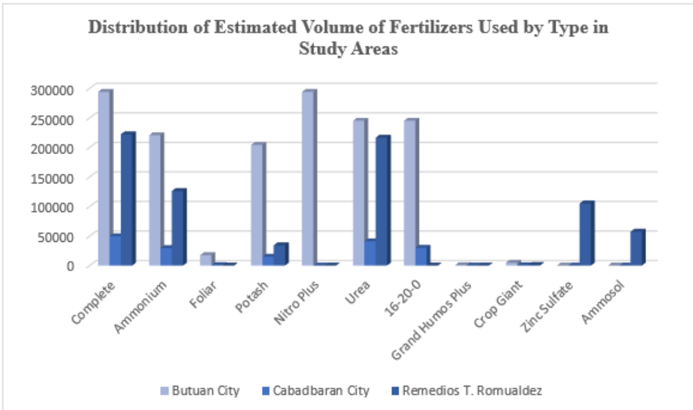

Fig. 14. Distribution of Estimated Volume of Fertilizers Used in the Study Area

3.4 Potential Waste Stream Map

The spatial risk assessment identifies high-risk pesticide and fertilizer runoff zones, mainly in flat, poorly drained areas near irrigation networks and water bodies. High-risk pesticide and fertilizer runoff zones are concentrated in flat, poorly drained areas near irrigation networks, increasing contamination risks. Flat terrains accumulate chemicals, while steeper slopes accelerate transport downstream. Poor drainage heightens groundwater contamination, emphasizing the need for integrated waste management. Solutions like improved drainage systems and riparian buffers can help mitigate environmental impacts in rice-producing areas.

Fig. 15 shows the agricultural waste accumulation zones, focusing on pesticide and fertilizer runoff risks. The Potential Waste Stream Map reveals that 0.2016% of rice areas fall into Low-Risk Streams, 74.5186% into Moderate-Risk Streams, 24.3927% into High-Risk Streams, and 0.8871% into Very High-Risk Streams, as shown in Figs. 16 and 17. These findings stress the need for targeted waste management interventions in high-risk areas to mitigate environmental impacts.

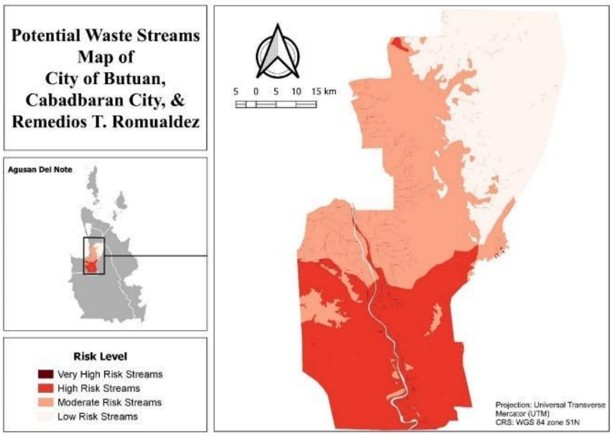

Fig. 15. Potential Waste Stream Map

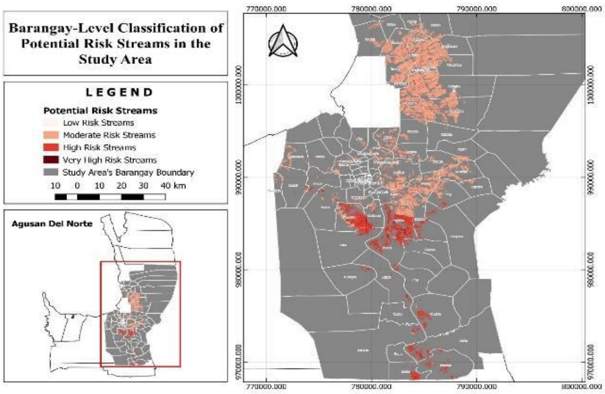

Fig. 16. Barangay-Level Classification of Potential Risk Streams Map in the Study Area

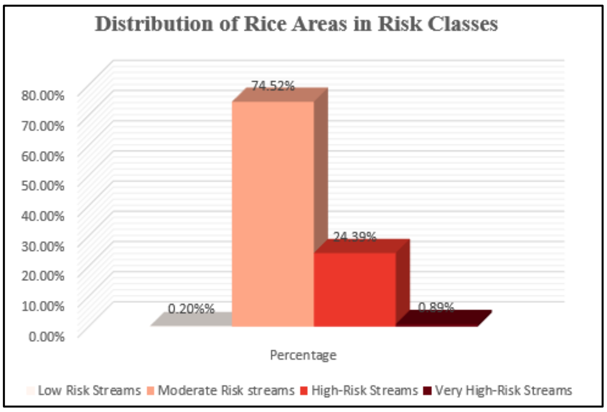

Fig 17. Distribution of Rice Areas per Risk Classes

3.5 Pesticides and Fertilizer Utilization Potential Waste Streams Map

Figs. 18, 19, and 20 illustrate the spatial distribution of herbicide, insecticide, and fungicide applications across risk classes in rice fields. In Fig. 18, herbicide utilization reaches 830.83 kg, primarily in the southern and central rice-growing areas, aligning with "High Risk" and "Moderate Risk" zones. Risk classifications—light pink (low risk), light red (moderate risk), dark red (high risk), and very dark red (very high risk) highlight vulnerable locations. The correlation between intensive pesticide uses and high-risk areas underscores the need for site-specific interventions balancing agricultural productivity with environmental sustainability.

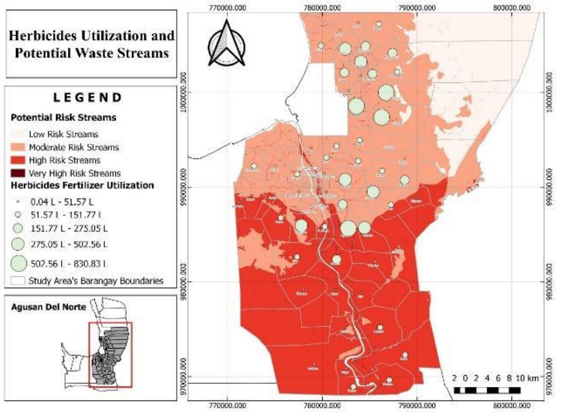

Fig. 18. Herbicides Utilization and Potential Waste Streams Map in the Study Area

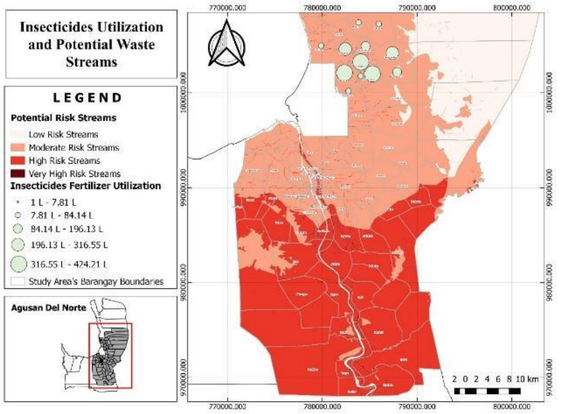

Fig. 19. Insecticides Utilization and Potential Waste Streams Map in the Study Area

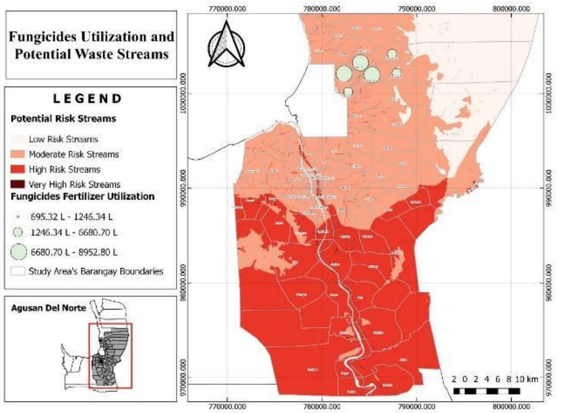

Fig. 20. Fungicide Utilization and Potential Waste Streams Map in the Study Area

4. CONCLUSIONS AND RECOMMENDATIONS

The study comprehensively assessed rice production waste streams in Agusan del Norte using geospatial technologies, achieving high mapping accuracy (98.87% overall, 0.96 kappa coefficient). Butuan City recorded the highest yield, followed by Remedios T. Romualdez and Cabadbaran City, with low-lying terrains and irrigation systems supporting productivity. The risk assessment revealed waste accumulation in poorly drained soils, with

74.52% of rice areas in moderate-risk streams, 24.39% in high-risk streams, and 0.88% in very high-risk zones. Pesticide and fertilizer usage varied across municipalities, with Butuan City practicing moderate chemical application, Remedios T. Romualdez exhibiting intensive use, and Cabadbaran City relying minimally on synthetic inputs. These findings highlight the need for localized interventions to optimize soil fertility management while mitigating environmental risks. Sustainable waste management strategies—composting, improved drainage, and riparian buffers—were identified as essential solutions.

Policies should regulate chemical use, establish buffer zones in high-risk areas to enhance sustainable rice production, and educate farmers on integrated pest management. GIS-based monitoring, improved drainage, and centralized composting facilities should be prioritized, while refining spatial analysis with high-resolution DEM datasets will optimize risk assessments. Future research should incorporate drone technology for real-time waste tracking and assess long-term pesticide runoff effects, ensuring scalable solutions for rice-producing regions while safeguarding environmental resources.

5. REFERENCES

[1] Sajonia Jr, Edgardo Ricardo B., and Anamarie P. Sajonia. "Yield Estimation of Major Crops in Butuan City, Agusan del Norte Using Geospatial Techniques." International Exchange and Innovation Conference on Engineering & Sciences, 2024.

[2] Asube, Lorie Cris S., and Roland E. Otadoy. "The Use of Geospatial Techniques to Estimate Rice Production as a Measure for Waste Analysis: A Review." International Exchange and Innovation Conference on Engineering & Sciences, 2024.

[3] A. M. Favis, C. K. G. Gonzales, and A. E. Lareza, "Addressing Rice Waste in University Cafeterias Using Material Flow Analysis and System Dynamics Modeling," *Philipp J Sci*, vol. 151, no. 3, pp. 1027–1047, Jun. 2022, doi: 10.56899/151.03.20.

[4] A. G. Apdohan, R. P. Varela, and R. M. Balanay, "Climate Risk Vulnerability Assessment of the Major Crops in the Province of Agusan Del Norte, Philippines",doi: 10.5194/isprs-archives-XLVI-4-W6-2021-27-2021.

[5] Japitana, Michelle V., Rex G. Parro, Stephanie Mae S. Albores, and Lorie Cris S. Asube. "Synergistic Paradigms: Developing R&D and Extension Framework for Sustainable Agrifood Systems." International Exchange and Innovation Conference on Engineering & Sciences, 2024.

[6] R. M. Santiago, R. Gustilo, G. Arada, E. Magsino, and E. Sybingco, "Performance Analysis of Machine Learning Algorithms in Generating Urban Land Cover Map of Quezon City, Philippines Using Sentinel-2 Satellite Imagery," *2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM2021*,2021,doi:10.1109/HNICEM54116.2021.9731856.

[7] D. Xu and M. Zhang, "Mapping paddy rice using an adaptive stacking algorithm and Sentinel-1/2 images based on Google Earth Engine," *Remote Sensing Letters*, vol. 13, no. 4, pp. 373–382, Apr. 2022, doi: 10.1080/2150704X.2022.2027543.

[8] R. K. Singh, J. Rizvi, M. D. Behera, and C. Biradar, "Automated crop type mapping using time-weighted dynamic time warping-A basis to derive inputs for enhanced food and Nutritional Security," *Current Research in Environmental Sustainability*, vol. 3, Jan. 2021, doi: 10.1016/J.CRSUST.2021.100032.

[9] P. M. Atkinson, "Spatial Scale, Problems of," *Encyclopedia of Social Measurement, Three-Volume Set*, vol. 3, pp. V3-639-V3-648, Jan. 2004, doi: 10.1016/B0-12-369398-5/00355-8.

[10] "Fundamentals of georeferencing a raster dataset—ArcMap | Documentation." Accessed: Dec.08,2024.[Online]. https://desktop.arcgis.com/en/arcmap/latest/manage-data/raster-and-images/fundamentals-for-georeferencing-a-raster-dataset.htm

[11] "NoData and how it affects analysis—ArcMap | Documentation." Accessed: Dec. 08, 2024. [Online]https://desktop.arcgis.com/en/arcmap/latest/extensions/spatial-analyst/performing-analysis/nodata-and-how-it-affects-analysis.htm

[12] "Converting surface data to vector data—ArcMap | Documentation." Accessed: Dec. 08, 2024.[Online].https://desktop.arcgis.com/en/arcmap/latest/extensions/3d-analyst/converting-surface-data-to-vector-data.htm

[13] J. I. Newkirk *et al.*, "Wild Rice River Watershed Monitoring and Assessment Report Minnesota Pollution Control Agency Authors MPCA Wild Rice River Watershed Report Team," 2017, Accessed: Aug. 29, 2024. [Online]. www.pca.state.mn.us.

[14] A. Pradhan, M. P. Pradhan, and R. Pradhan, "An automated approach towards generation of stream attributes for use in GIS applications," *Multimed Tools Appl*, vol. 83, no. 7, pp. 20307–20356, Feb. 2024, doi: 10.1007/S11042-023-16426-2/METRICS.