Geospatial Analysis of Rice Production: Integrating Precision Mapping and Waste Assessment Using Remote Sensing and GIS Technologies in Remedios T. Romualdez (RTR), Agusan del Norte

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Geospatial Analysis of Rice Production: Integrating Precision Mapping and Waste Assessment Using Remote Sensing and GIS Technologies in Remedios T. Romualdez (RTR), Agusan del Norte

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Abstract: *This study uses remote sensing and GIS technologies to analyze rice production and related waste in Remedios T. Romualdez (RTR), Agusan del Norte, using an integrated geospatial approach. To estimate spatial variations in productivity, rice cropland maps and yield models were created using field data and imagery from Landsat missions. To estimate rice yield, a simplified regression model that combined NDVI, EVI, and SAVI was developed; it produced an* R^2 *of 0.733 and an RMSE of 0.086 MT/pixel. The temporal maps of rice yield and waste from 2000 to 2020 were then created by applying this model to historical imagery. The findings clearly demonstrated the significant spatiotemporal variability in yield and waste across RTR, with some years and regions consistently exhibiting higher productivity and corresponding waste. This analytical framework offers a highly scalable solution for precision agriculture, effectively promoting sustainable resource use and efficient waste management practices in rice production.*

Keywords: Rice, Waste, Remote Sensing, GIS, Google Earth Engine

1. INTRODUCTION

Rice, a staple food for billions worldwide, necessitates innovative approaches to enhance production efficiency and minimize waste across its production stage, especially as rising global populations and food demand intensify the challenge of food waste [1]. With the global population nearing 10 billion by 2050, increasing food demand will place significant pressure on agricultural resources despite environmental constraints [2]. Rice production systems face several critical challenges, notably inefficiencies, yield variability, and significant waste generation. Production inefficiencies often result from limited adoption of advanced agricultural technologies and suboptimal resource management, including excessive water and fertilizer use, which can degrade the environment and elevate production costs [3]. These factors create a complex scenario for agriculture, necessitating innovative strategies and sustainable practices to ensure food security and the sector's resilience in the face of these constraints.

Traditional agricultural practices often fall short in addressing the complexities of rice cultivation, particularly in diverse and rapidly changing environments, necessitating a shift towards precision management practices that integrate various components into high-yield, high-efficiency crop management systems [4]. Information emphasizes the significant need to monitor crop growth and health and implement timely intervention strategies. These measures are vital for improving agricultural crop production and reducing the consumption of input resources. Such approaches are essential to achieve global food security goals, indicating a strategic shift towards more efficient and sustainable agricultural practices.

Recent advancements in sensor technology, communication systems, and data analysis have enhanced sustainable agricultural practices, reduced resource use, and prevented future losses, supporting higher and sustainable yields to meet global food security objectives. Geospatial technologies, along with data-driven methods, are now crucial for crop and soil analysis, playing a vital role in global food security [5]. When integrated with other sources of evidence, these technological solutions provide data-driven insights and information for precise, site-specific crop management, aiming to enhance production levels [6]. Geospatial technologies, including remote sensing and Geographic Information Systems, play a crucial role in applications such as crop identification, cropland mapping, yield estimation, inversion of critical parameters, disaster monitoring, and precision farming [5].

The integration of remote sensing and GIS technologies offers a transformative approach to understanding and optimizing rice production systems [7]. Among remote sensing datasets, Landsat is widely utilized in rice mapping due to its long-standing digital archive, offering moderate spatial resolution along with consistent spectral and radiometric quality [8]. Integrating precision mapping and waste assessment through remote sensing and GIS technologies holds immense potential for transforming rice production systems towards greater efficiency, sustainability, and resilience.

Despite significant advancements in geospatial technologies, several research gaps remain concerning their integrated application to precision mapping and rice waste assessment. Many existing studies have separately focused either on precision agriculture for yield optimization or on waste management analysis, but comprehensive integration of both elements is relatively underexplored [9]. Additionally, there is a notable lack of standardized methodologies and protocols for systematically combining remote sensing datasets and GIS-based spatial analysis, specifically aimed at assessing rice waste in rice production [10]. This gap is particularly evident in developing countries, where limited technical capacity and fragmented data resources further complicate integrated spatial analysis efforts [11]. Addressing these limitations by developing robust, integrated approaches using remote sensing and GIS can significantly contribute to sustainable rice production and improved waste management practices.

The primary aim of this study is to integrate precision mapping and waste assessment of rice production through the application of Remote Sensing and Geographic Information Systems (GIS). Specifically, the research seeks to accurately map rice production areas in Remedios T. Romualdez (RTR), Agusan del Norte, from 2000, 2010, 2020, and the recent year 2023, quantify production efficiency, and systematically assess waste generation in the rice production stage. The integration of these advanced geospatial techniques is expected to significantly enhance agricultural sustainability by enabling better resource management and waste reduction [11]. Additionally, the outcomes will support informed decision-making among stakeholders, policymakers, and farmers by providing reliable spatially-explicit data on rice production performance and waste hotspots, thereby promoting more efficient allocation of resources and ultimately contributing to increased productivity and environmental conservation [10]. This research is anticipated to bridge existing methodological gaps and foster more sustainable and resilient rice production systems.

2. METHODOLOGY

2.1 Study Area

The Caraga Region, which includes the municipality of Remedios T. Romualdez (RTR) in Agusan del Norte, is recognized as a major rice-producing area in the region. RTR is located at approximately 9° 03′ North latitude and 125 35’ East longitude, as shown in Fig. 1. Covering a total land area of 79.15 square kilometers, RTR is composed of eight barangays and had a population of 17,155 as of the 2020 census, according to the Philippine Statistics Authority [14]. RTR presents a valuable case for rice mapping study because of its complex agricultural landscape and diverse socio-economic conditions. The municipality features a mix of topographical variations, soil types, and water systems, all of which contribute to the spatial diversity in rice farming practices. A detailed understanding of these spatial variations is essential for optimizing agricultural resource allocation, improving crop productivity, and promoting sustainable land management strategies. Additionally, such insights are critical for assessing and managing rice waste, enabling the development of efficient waste utilization practices that support environmental sustainability and circular agriculture.

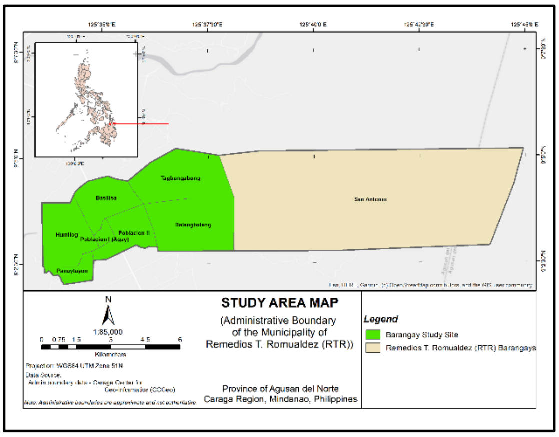

Fig. 1. Location map of Remedios T. Romualdez (RTR)

2.2 Mapping Rice Croplands in Remedios T. Romualdez (RTR), Agusan del Norte

Rice mapping was initiated using the Google Earth Engine (GEE) platform. This study utilized multispectral Landsat imagery to map rice crops across key years: 2000, 2010, 2020, and the recent year 2023. In order to effectively distinguish rice areas from non-rice areas, the images must have less cloud cover and be taken during the pre-planting stage of rice crops. The satellite images were then used for image classification using Random Forest classifier, and the classified image was subjected to accuracy assessment. The final classified images were then refined using Google Earth to correct most of the misclassed pixels of rice and non-rice areas. The refined classified images were then used to extract the rice paddies in the study site.

2.3 Development of Rice Yield Model

2.3.1 Rice Production Data

The methodology is a spatially explicit approach to rice yield mapping, using the combined integration of field-acquired data and remotely sensed imagery. Initially, the process commences with rice production datasets (only for the year 2023) obtained from the Department of Agriculture (DA)-Caraga, which crucially include GPS tracks delineating the spatial extent of individual rice fields. These GPS tracks, originally represented as LineString geometries, underwent a transformation into polygon shapefiles, a necessary step to facilitate area-based spatial analyses and subsequent calculations. Attribute editing is then performed to standardize and validate the data by correcting errors and filling in the missing entries, followed by a crucial step of dissolving geometries that share common attributes to reduce redundancy and create more homogeneous spatial units.

For each resultant polygon, a geometric attribute representing the area is computed, providing a fundamental parameter for subsequent yield estimation and spatial analysis, and these polygons are converted into point features. This conversion is strategically implemented to ensure compatibility and facilitate integration with raster-based remote sensing data sources, such as Landsat imagery, which inherently represent data as a grid of pixel values. This methodology underscores the importance of data preprocessing and geometric transformations in preparing geospatial data for advanced analysis.

The conversion of rice field boundaries from line geometries to polygons enables the calculation of area, a critical parameter for yield estimation and spatial analysis, which marks a pivotal step towards integrating field data with remote sensing techniques for enhanced accuracy. The utilization of GPS tracks from DA-Caraga not only provides precise spatial delineation of rice fields but also allows for the creation of a georeferenced database that can be continuously updated and improved. Attribute editing plays a crucial role in ensuring data quality and consistency, addressing potential errors or inconsistencies in the original dataset, thus enhancing the reliability of subsequent analyses. The dissolution of geometries with shared attributes streamlines the dataset, reducing redundancy and creating a more manageable and interpretable spatial representation of rice cultivation patterns.

This method ensures that the final dataset is optimized for integration with remote sensing data, which typically involves raster-based analysis techniques that benefit from point-based representations of field locations.

2.3.2 Satellite Data Gathering and Pre-processing

Satellite photos captured during the heading stages of rice growth are ideal for modeling rice yield [15]. Another processing to be conducted on the corrected images is extracting the predictor variables: multispectral bands, vegetation indices, and land surface temperature. This study applied the different Landsat missions corresponding to each year's targets. Vegetation indices are mathematical formulations used to estimate crop yields, including rice.

This study utilized various vegetation indices, which include Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and Green Vegetation Index (GVI). Land surface temperature (LST) is increasingly important for understanding the thermal dynamics of rice-growing regions and their influence on rice yield. As a key indicator of environmental conditions, LST is a proxy for assessing crop health, stress levels, and growth stages throughout the rice growing season. Twelve predictor variables were used in the Landsat 8 image, while a total of eleven were extracted from the Landsat 5 and Landsat 7 images.

2.3.3 Rice Yield Modelling

The pixel values for each predictor variable were extracted from multitemporal Landsat images using the center coordinates of the plots that were gathered, or 294 training data points. To determine the relationship between the predictor variables and the actual yield data, the Pearson correlation coefficient (r) was used. The actual yield from the Landsat predictor variables was then modeled using Multiple Linear Regression (MLR) and the Ordinary Least Squares (OLS) method. The accuracy of the regression model's estimation of rice yield was evaluated. To assess the yield model, the Root Mean Square Error (RMSE) and the coefficient of determination, or (R^2), were computed.

2.3.4 Estimation and Mapping of Rice Yield and Accuracy Assessment

The regression model that was developed was used to estimate the rice yield. The goal of the equation-based model was to generate an image where the estimated yield value was represented by the value of each pixel. The seventy-four (74) validation plots with real yield data were used to evaluate the accuracy of the rice yield maps produced using the derived model. Calculations were made to determine the R^2 and RMSE between the observed and predicted yields. Additionally, the derived model's ability to forecast rice yield was taken into account and examined.

2.4 Rice Yield to Rice Waste Conversion Model

The waste conversion model created from the waste generated from the stages of rice production is necessary to convert rice yield to rice waste. The various stages of rice cultivation and processing result in various components that make up rice waste. The above-ground plant matter that remains after rice grains are harvested is referred to as straw. The outer protective layer of the grain is called husk, and the layer that is removed during milling to create white rice is called bran. Grain fragments that break during milling make up broken rice.

Additionally, there are losses from processing, such as broken grains produced during handling and milling. Grain lost during handling or left in the field is referred to as unharvested or spilled rice. For every ton of harvested rice paddy, roughly 1.35 tons of rice straw are produced in the field, according to Moraes et al. (2014) [16]. Then, 200 kg, 100 kg, and 140 kg of rice husk, bran, and broken rice are produced for every ton of paddy rice that is industrially processed.

3. RESULTS AND DISCUSSIONS

3.1 Rice Maps

The demarcated boundaries of rice plantations in RTR for each year target are depicted in Fig. 2 and Fig. 3. The total area of classified rice paddies, as well as its overall accuracy result, is presented in Table 1. The delineated rice areas ranged from 1,369.61 ha to 1,481.70 ha, with the highest extent observed in 2010. Overall classification accuracy improved slightly over time, reaching 96.84% in 2020, indicating reliable mapping performance.

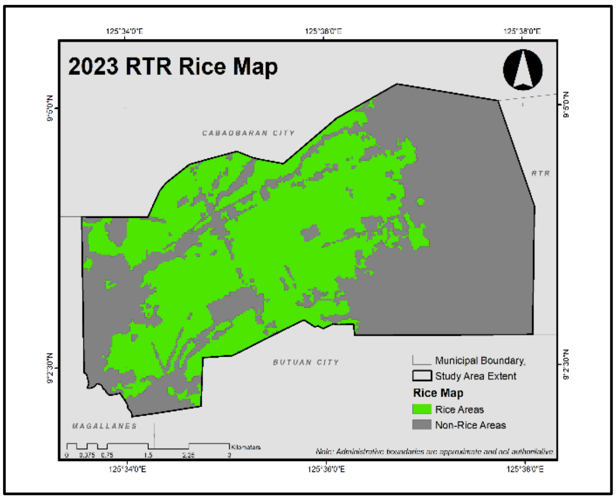

Fig. 2. Rice map of RTR for year 2023

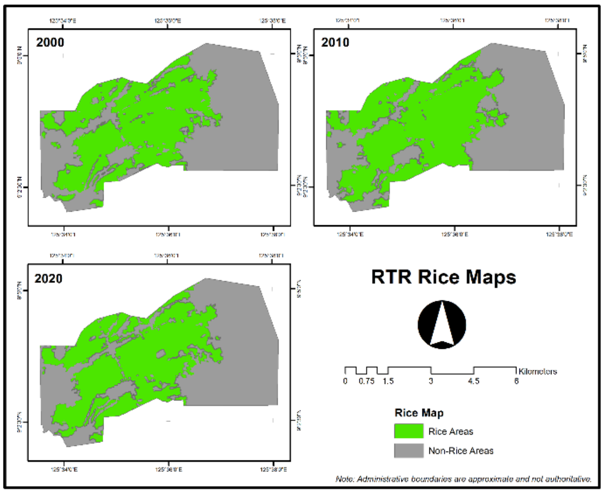

Fig. 3. Rice maps of RTR for years 2000, 2010, and 2020

Table 1. Delineated rice areas and accuracy per year

Year	Delineated Rice Area (ha)	Overall Accuracy (%)
2000	1,369.61	93.97
2010	1,383.02	95.51
2020	1,481.70	94.94
2023	1,394.73	96.84

3.2 Correlation of Landsat-based Predictor Variables with Observed Yield

Fig. 4 shows a graph of the predictor variables' correlation coefficients (r), which varied from -0.663 to 0.815. Just four (4) of the twelve Landsat 8 predictor variables—Band 5, NDVI, EVI, and SAVI—exhibited a strong linear correlation with the yield data. With r-values of 0.616, 0.815, 0.738, and 0.756, respectively, these four variables show a significant correlation with the observed yield.

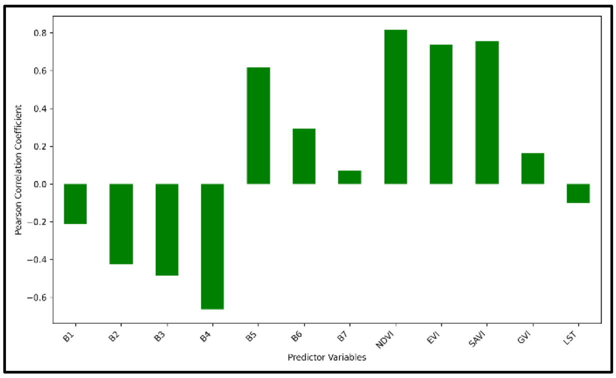

Fig. 4. Correlation of Landsat 8-derived predictor variables to the observed rice yield

3.3 Rice Yield Model Development

Several spectral bands and vegetation indices obtained from remote sensing data were used in multiple linear regression analysis to forecast rice yield in the study area. First, a detailed model was created that included vegetation indices (NDVI, EVI, SAVI, GVI, and LST) and spectral bands (B1 to B7). However, only three indices—NDVI, EVI, and SAVI—were determined to be significant predictors at the 95% confidence level ($p < 0.05$) following an evaluation of each variable's statistical significance.

The resulting simplified regression model is expressed as:

$$Predicted\ Yield = 1.2701 - (3.0455 * NDVI) - (7.2008 * EVI) + (14.6425 * SAVI)$$

With a coefficient of determination (R^2) of 0.733, this model suggests that these three indices account for roughly 73.3% of the variation in rice yield. Furthermore, a comparatively low prediction error was suggested by the root mean square error (RMSE), which was determined to be 0.086 metric tons per pixel (MT/pixel). Despite being frequently used in vegetation studies, Band 5 (NIR) was disregarded because it was redundant with indices such as NDVI and SAVI and lacked statistical significance ($p > 0.05$). The simplified model prioritizes vegetation indices that more accurately reflect crop vigor and productivity while avoiding multicollinearity. This improves the model's resilience when utilizing remote sensing data to estimate rice yield spatially.

3.4 Estimated Rice Yield Maps of RTR

The estimated rice yield in RTR (Remedios T. Romualdez), Agusan del Norte, is shown spatially in Fig. 5 and Fig. 6 for the years 2000, 2010, 2020, and the most recent data from 2023. These maps, which were produced using remote sensing and geospatial analysis methods, provide a quantitative and visual understanding of the variability of spatial yield over time.

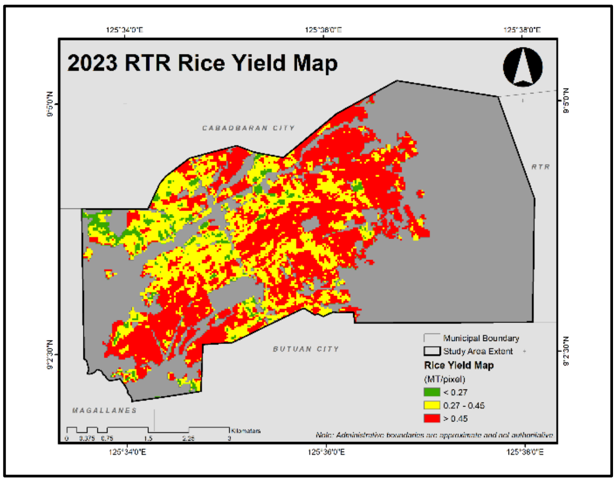

Fig. 5. Estimated rice yield map of RTR for year 2023, classified according to the level of yield

Three categories—low (<0.27 MT/pixel), moderate (0.27–0.45 MT/pixel), and high (>0.45 MT/pixel)—are used to classify yield levels in detail on the 2023 RTR Rice Yield Map. High-yielding zones are more dispersed and concentrated in some areas, especially in the northeastern and southwestern regions of the study area, while low to moderate rice yields predominate to other areas of the municipality, according to the spatial pattern. These differences in spatial yield point to the impact of regional biophysical and socio-environmental elements like topography, access to irrigation, and land management techniques.

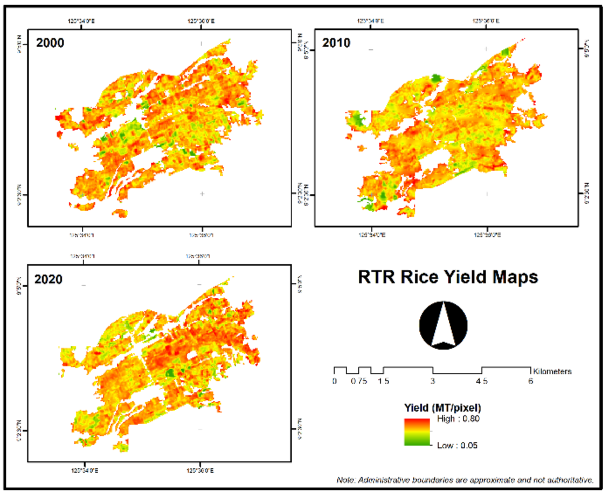

Fig. 6. Estimated rice yield maps of RTR for years 2000, 2010, and 2020

A temporal series of estimated rice yields for 2000, 2010, and 2020 is shown in Fig. 6. Since no actual yield data were recorded during these prior years, these yield maps were created using the simplified regression model. Significant interannual variability is revealed by a comparative analysis. The yield distribution looks more evenly moderate in 2000, but the 2010 map shows a slight yield decline, especially in the eastern and central regions. By 2020, however, yield has clearly improved, with many regions exhibiting moderate to high productivity.

3.5 Accuracy Assessment of the Estimated Rice Yield

The scatterplot between observed and predicted yield and its coefficient of determination (R^2) of 0.4105 is shown in Fig. 7. The garnered R^2 value means that the model has the slight potential to estimate rice yield. Also, the RMSE of the validation plots has a value of 0.07 MT/pixel, which denotes that the final yield model is moderately good and acceptable in estimating rice yield in the study area.

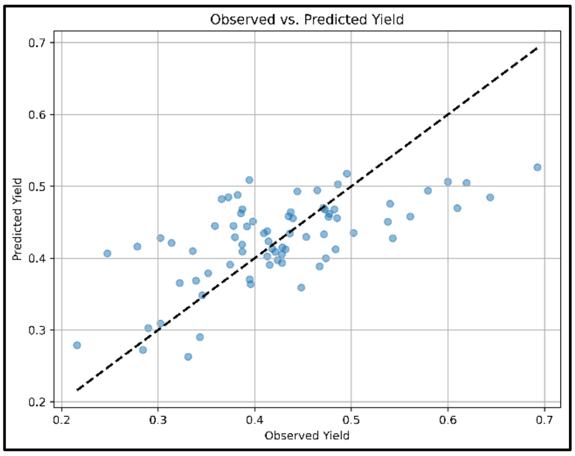

Fig. 7. Scatter plot between observed and predicted yield of the validation plots

3.6 Estimated Rice Waste Maps

In this step, the researchers used mathematical relationships derived from established conversion factors to transform rice yield maps into corresponding rice waste models within a GIS environment. By applying consistent conversion factors proportionate to the metric tons (MT) of paddy rice, the rice yield values expressed in MT per pixel were translated into spatial estimates of rice waste. This process resulted in new raster layers representing total rice waste, which offer insight into the spatial extent and intensity of agricultural residues generated from rice production.

Fig. 8 and Fig. 9 display the estimated rice waste distribution in RTR for the years 2000, 2010, 2020, and 2023. The 2023 RTR Rice Waste Map (Fig. 8) illustrates the current state of waste generation, with pixel values ranging from approximately 0.09 to 1.432 MT per pixel. The spatial pattern highlights more significant waste concentrations in northeastern and southwestern parts of the study area, coinciding with higher-yielding zones as seen in the corresponding rice yield map. This strong spatial alignment emphasizes the direct proportionality between rice production and waste generation.

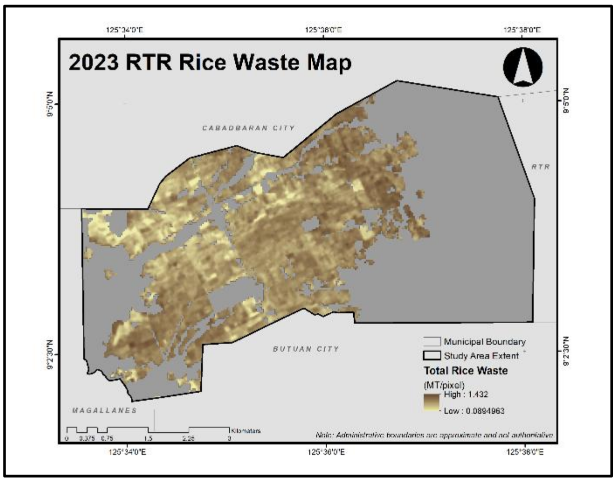

Fig. 8. Estimated rice waste map of RTR for year 2023

Fig. 9 presents estimated rice waste maps for the years 2000, 2010, and 2020. In 2000, waste generation was relatively moderate and evenly distributed. By 2010, a slight decrease in rice waste was observed in some central and western parts of the study area, likely reflecting lower yields during that period. In contrast, the 2020 map shows a resurgence in rice waste density, particularly in the eastern regions, consistent with improvements in rice yield as seen in the previous figure.

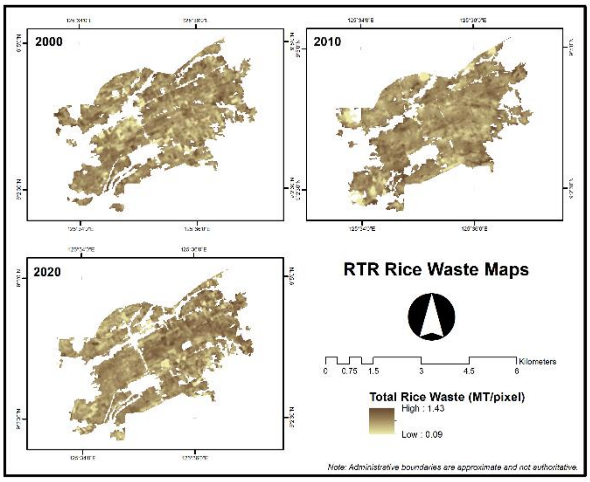

Fig. 9. Estimated rice waste maps of RTR for years 2000, 2010, and 2020

4. CONCLUSIONS AND RECOMMENDATIONS

This study showed how useful it is to combine remote sensing and GIS to create a spatially explicit model for estimating rice yield and evaluating waste in RTR. With a high correlation and manageable error levels, the NDVI, EVI, and SAVI-based simplified regression model was successful in forecasting rice yield. Significant spatiotemporal variability, influenced by biophysical and management factors, was revealed by the yield and waste maps that were generated. For local stakeholders to make well-informed decisions about crop management and sustainability practices, these insights are essential.

Recommendations include integrating socio-economic variables to better understand yield variability, adding more satellite datasets with higher spatial and temporal resolution, and extending the model to other rice-producing regions for wider validation. In order to improve food security through data-driven agricultural planning and waste reduction strategies, policymakers and agricultural agencies are urged to implement such geospatial frameworks.

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