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# Reliable Assessment of Long-Term Land Use Change to Support Sustainable Watershed Management Using Multi-Sensor Landsat Imagery

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**Abstract:** Land use change analysis is widely applied in watershed studies, yet its reliability is often limited when multi-temporal classification accuracy is not systematically evaluated. This study aims to assess long-term land use change while emphasizing the accuracy and reliability of change detection in the Petung Watershed, East Java, Indonesia. Multi-temporal Landsat imagery from Landsat 7, 8, and 9 (2005–2024) was analyzed using a supervised classification approach implemented in ArcGIS. Classification accuracy was evaluated using a confusion matrix and the Kappa coefficient to ensure temporal consistency and methodological reliability. The results indicate a clear shift in land use patterns, characterized by a continuous decline in vegetation cover and a substantial expansion of agricultural and built-up areas. Classification reliability is supported by Kappa coefficient values ranging from 0.701 to 0.829, corresponding to substantial to almost perfect agreement, with the highest accuracy achieved in the later observation years. These findings demonstrate that the proposed supervised, GIS-based framework provides a reliable and replicable approach for accurately measuring long-term land use change at the watershed scale. While the methodology can be applied to other regions, the observed land use dynamics are specific to the Petung Watershed and reflect local environmental and anthropogenic conditions.

**Keywords:** Kappa coefficient; Land use change; Landsat imagery; Petung watershed; Supervised classification

## Introduction

Land use change is a critical global environmental issue due to its substantial impacts on ecosystem integrity, watershed processes, and landscape sustainability. Rapid population growth, agricultural expansion, and urbanization have intensified land transformation, particularly in tropical regions where environmental systems are highly dynamic and vulnerable. Consequently, land use and land cover (LULC) change analysis has become a central tool for monitoring spatial and temporal landscape dynamics using remote sensing and geographic information systems (Tiwari et al., 2017; Tran et al., 2015; Yan et al., 2015). Despite its widespread application, land use change research continues to face major challenges, including spatial heterogeneity, temporal inconsistency, and uncertainty arising from sensor differences and classification procedures, which can obscure actual land use trajectories and reduce the reliability of long-term change detection (Otukei et al., 2010; Zhu et al., 2014).

Although methodological advancements have improved land use change analysis, its performance remains constrained by several persistent limitations. Many studies rely on single-sensor datasets, short temporal coverage, or inconsistent classification frameworks, leading to reduced comparability across time and increased classification uncertainty (Chaves et

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al., 2020; Mtibaa et al., 2016). Recent research highlights the importance of standardized image pre-processing, multi-temporal analysis, and robust accuracy assessment to improve LULC mapping reliability (Saraf et al., 2024; Sembosi, 2023). In addition, comparative studies demonstrate that different classification techniques can produce substantially different results, emphasizing the need for systematic performance evaluation and calibration (Tikuye et al., 2023). However, a clear research gap remains in evaluating how accuracy calibration—particularly using agreement-based indices such as the Kappa coefficient—can enhance the reliability and comparability of supervised land use change analysis across long-term, multi-sensor Landsat datasets. However, many watershed-scale land use change studies still lack systematic control of temporal consistency and classification accuracy, particularly when integrating multi-sensor Landsat data. Differences in sensor characteristics and validation procedures may result in apparent land use changes that reflect classification uncertainty rather than actual landscape dynamics.

This study is based on the methodological hypothesis that the consistent application of supervised classification calibrated using the Kappa Coefficient across multi-sensor Landsat imagery (Landsat 7, 8, and 9) can improve the reliability of long-term land use change analysis. The central problem addressed in this study is the limited reliability of land use change analysis when classification accuracy and temporal consistency are not rigorously controlled. This study hypothesizes that the consistent application of a supervised classification approach across multi-temporal Landsat imagery, combined with systematic accuracy calibration using the Kappa coefficient, can significantly improve the reliability of watershed-scale land use change analysis. To address this problem, this research proposes a standardized GIS-based framework that integrates harmonized image pre-processing, supervised classification, and accuracy assessment. The main contribution of this study lies in demonstrating a robust and replicable methodological approach that enhances the credibility and comparability of land use change information relative to previous studies that employed less standardized or shorter-term analytical frameworks (Saraf et al., 2024).

The novelty of this research lies in the development of a standardized, robust, and replicable GIS-based framework that integrates harmonized image pre-processing, supervised classification, and systematic accuracy calibration across a long-term, multi-sensor Landsat dataset. The objective of this study is to analyze the spatiotemporal dynamics of land use change in the Petung Watershed from 2005 to 2024 using multi-temporal Landsat imagery. The methodological framework consists of standardized image pre-processing, land use classification using a supervised method implemented in ArcGIS, and accuracy evaluation through a confusion matrix and the Kappa coefficient. Subsequently, land use change analysis is conducted through multi-temporal comparison of classified maps to identify spatial patterns, temporal trends, and dominant land use transitions within the watershed, thereby contributing to a more reliable assessment of long-term land use dynamics.

## Method

This study was conducted in the Petung Watershed (DAS Petung), located in Pasuruan Regency, East Java Province, Indonesia, with a total area of approximately 141.729 km². The Petung Watershed represents a typical watershed in East Java that has experienced notable land use dynamics over recent decades. To examine the spatial and temporal characteristics of land use, this study employed multi-temporal Landsat satellite imagery as the primary dataset. Landsat data from Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS), and Landsat 9 Operational Land Imager-2/Thermal Infrared Sensor-2 (OLI-2/TIRS-2) were utilized to produce land use maps using a supervised classification approach, thereby enabling a consistent assessment of land use distribution and changes within the Petung Watershed over the study period.

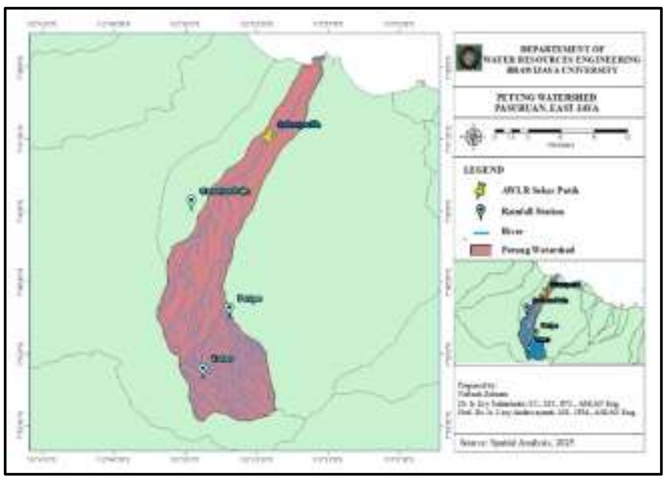


**Figure 1.** Petung Watershed

*Data*

*Landsat 7, 8, 9 Satellite Imagery from USGS*

This study utilized multi-temporal Landsat satellite imagery obtained from the United States Geological Survey (USGS) to analyze land use dynamics in the Petung Watershed. The dataset includes imagery from

Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS), and Landsat 9 Operational Land Imager-2/Thermal Infrared Sensor-2 (OLI-2/TIRS-2). Landsat 7 ETM+ provides medium-resolution multispectral data suitable for long-term land use analysis, while Landsat 8 and Landsat 9 offer improved radiometric performance and spectral sensitivity, enhancing the consistency and reliability of multi-temporal land use classification. All images were selected from comparable acquisition periods to minimize seasonal variation.

*Administrative Map of the Petung Watershed*

The administrative map of the Petung Watershed was used to define the spatial boundary of the study area. The watershed boundary data were available in vector format as shapefile (.shp) for spatial analysis and Keyhole Markup Language (.kml) format for visualization in Google Earth Pro. This boundary dataset was employed to clip the Landsat imagery and ensure that all analyses were spatially restricted to the Petung Watershed.

*Models*

This study uses several methods in land use classification, namely:

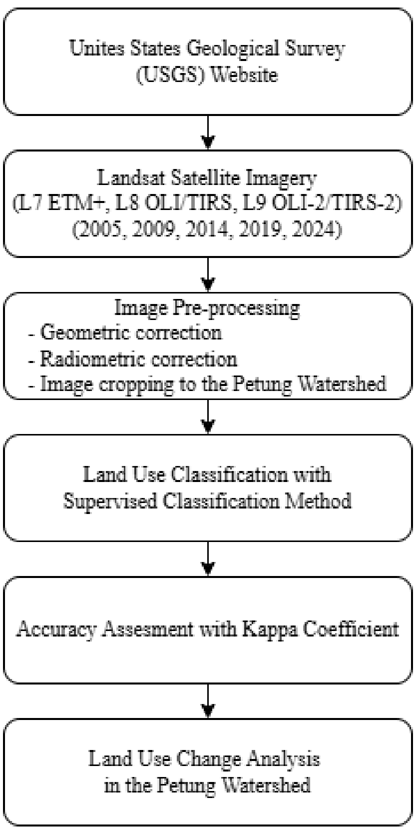


**Figure 2.** Flowchart of the land use change methodology in the Petung Watershed

*Image Pre-processing*

Multi-temporal Landsat imagery must undergo a rigorous pre-processing workflow to ensure geometric consistency, radiometric comparability, and spatial alignment across acquisition years. This typically starts with geometric correction/co-registration to a common coordinate system to reduce displacement caused by sensor geometry, topography, and Earth curvature; such co-registration is essential for reliable change detection and multi-temporal mapping (Behling et al., 2014; Elbakary et al., 2025). The workflow then proceeds with consistent data management (e.g., harmonized projection and spatial extent) so that inter-annual differences in land use can be attributed to real landscape dynamics rather than misregistration artifacts.

Radiometric harmonization is equally critical because inter-sensor and inter-date variability can bias class separability. A common approach is to apply radiometric calibration and atmospheric correction, including haze-reduction methods such as Dark Object Subtraction (DOS), to normalize reflectance behavior across time and sensors (Chettry, 2022; Wu et al., 2021). Additional steps—such as noise reduction and image enhancement—can improve the interpretability of surface features (Hurat, 2020; Liu et al., 2009), while subsetting and layer stacking facilitate the creation of comparable multi-band composites for subsequent classification and change analysis (Toma et al., 2023).

*Land Use Classification Using Supervised Method*

Landsat imagery provides a long-term, medium-resolution (30 m) archive that supports regional-scale land cover classification and multi-year land use monitoring, making it a cost-effective foundation for watershed-scale studies (Mohammady et al., 2015). Within supervised frameworks, the Maximum Likelihood Classifier (MLC) remains widely used because it estimates class membership probabilities based on training data distributions; when training samples are representative, MLC can achieve strong performance (Echeverría-Puertas et al., 2023) and has been applied effectively to distinguish forests, agricultural lands, and urban areas (Nguyen et al., 2019).

Recent advances increasingly highlight machine-learning classifiers—particularly Random Forest (RF) and Support Vector Machine (SVM)—as robust alternatives for complex landscapes. Evidence from watershed and Indonesia-focused applications indicates that RF can yield high overall accuracy using Landsat data (Fariz et al., 2025), while SVM often performs well for delineating subtle land cover transitions (Memon et al., 2024). Nonetheless, supervised mapping remains sensitive to training quality and spatial resolution constraints; Landsat's moderate resolution can obscure small or fragmented classes and increase confusion among spectrally similar categories, requiring careful calibration and validation to reduce misclassification risk (Phiri et al., 2017).

*Kappa Coefficient Index*

The Kappa coefficient extends accuracy evaluation by accounting for the agreement expected by chance, thereby providing a more discriminative reliability index for thematic maps. Empirical studies commonly report overall accuracy and Kappa jointly; for example, overall accuracy values around strong-performing classifiers and Kappa values near or above 0.8 have been used to indicate substantial agreement (Islami et al., 2022). Best-practice assessment further recommends reporting user/producer accuracy alongside Kappa to diagnose commission and omission errors (Rwanga et al., 2017), and comparative evidence frequently shows supervised approaches outperform unsupervised mapping in terms of Kappa-based agreement (Riegel et al., 2019; Yadav et al., 2022).

The Kappa Coefficient Index is used to measure the level of agreement between the classification results and reference data, which in this study is obtained from Google Earth. The Kappa Coefficient is calculated using the following formula:

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \quad (1)$$

Explanation:

$P_0$ = (Observed Agreement): The proportion of agreement observed between the classified map ang the reference data

$P_e$ = (Expected Agreement): The proportion of agreement expected by chance, based on the distribution of categories in the classified data and reference data

**Table 1.** Kappa Coefficient Index (Altman, 1999)

| Value of Kappa | Interpretation |
|---|---|
| < 0 | Poor |
| 0.01 – 0.20 | Slight |
| 0.21 – 0.40 | Fair |
| 0.41 – 0.60 | Moderate |
| 0.61 – 0.80 | Substantial |
| 0.81 – 1.00 | Almost Perfect |

The Kappa value ranges from −1 to 1, where a value of 1 indicates perfect agreement between the classified map and the reference data, a value of 0 indicates no agreement beyond that expected by chance, and a value less than 0 indicates agreement that is worse than would be expected by chance.

## Result and Discussion

*Downloading Landsat 7, 8, and 9 Image Data*

This study analyzes land use dynamics in the Petung Watershed using multi-temporal Landsat imagery from Landsat 7 ETM+, Landsat 8 OLI/TIRS, and Landsat 9 OLI-2/TIRS-2 acquired from the USGS. All images were subjected to standardized image pre-processing, including geometric correction, radiometric normalization, band compositing, and watershed-based clipping to ensure spatial and temporal comparability. Land use maps were generated using a supervised classification approach with consistent training samples across all observation years, producing five land use classes representing the dominant surface conditions. Classification reliability was evaluated using a confusion matrix and the Kappa coefficient to ensure acceptable thematic accuracy prior to analysis. Land use change analysis was then conducted by comparing classified maps across multiple time periods to identify spatial patterns, temporal trends, and dominant land use transitions within the Petung Watershed.

*Composite Landsat 7 Using ENVI 5.3*

To support consistent land use classification, Landsat bands should be organized into a standardized multi-band dataset through layer stacking/compositing, enabling subsequent interpretation and class separability analysis. A composite workflow consolidates relevant spectral bands into a single stack while maintaining consistent spatial extent and band ordering across years; this approach is particularly useful for time-series studies because it reduces operational complexity and improves comparability between observation periods (Toma et al., 2023). In practice, compositing is typically performed after geometric and radiometric preparations to ensure that the stacked bands represent comparable surface reflectance behavior rather than acquisition noise.

Within the same pre-processing pipeline, noise reduction and enhancement may be used to improve feature clarity before compositing and classification, supporting more stable spectral signatures for training and decision rules (Hurat, 2020). Atmospheric correction is also emphasized as a prerequisite for accurate surface characterization and reliable time-series comparison (Abdulwahid et al., 2025). Note: the file provides the compositing rationale (layer stacking) and its role in multi-temporal analysis, but it does not detail ENVI 5.3 button-by-button procedures; the paragraph here is therefore written to remain consistent with the documented scientific steps and citations.

*Land Use Change Analysis*

Land use change analysis in the Petung Watershed was conducted based on land use maps generated through a supervised classification approach implemented within the ArcGIS environment, ensuring consistency in class definition and spatial processing across all observation years. Classified maps derived from multi-temporal Landsat imagery were compared sequentially (2005, 2009, 2014, 2019, and 2024) to quantify spatiotemporal changes in land use area and distribution. This supervised, GIS-based framework enables systematic identification of the magnitude and direction of change for each land use class, including transitions among vegetation, agricultural land, open land, built-up areas, and water bodies. The methodological logic follows established land use and land cover (LULC) change-detection frameworks that integrate remote sensing classification outputs with GIS-based temporal comparison to interpret dominant land cover trajectories and landscape dynamics (Sembosi, 2023). Furthermore, the use of consistent supervised classification results within ArcGIS supports reliable temporal inference by minimizing classification bias across years, an approach that has been widely applied in time-series Landsat studies to reduce ambiguity in detected change signals when seasonal control and standardized processing are maintained (Yan et al., 2015).

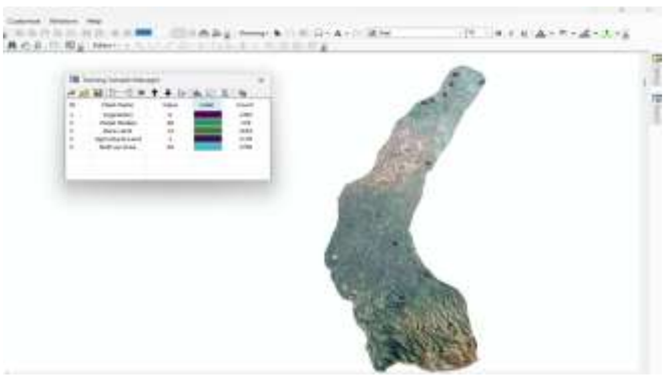

**Figure 3.** Land use map with supervised method in ArcGIS

*Accuracy Assesment Using Kappa Coeffiient Index*

Classification "calibration" in this context refers to ensuring that thematic maps meet acceptable reliability thresholds through systematic validation against reference samples. The study evaluates classification outputs using a confusion matrix and derives overall, producer's, and user's accuracy for each class; this design provides both aggregate reliability and class-specific performance diagnostics. The Kappa coefficient is then computed to quantify agreement beyond chance, ensuring that the final classified maps are sufficiently robust for downstream change analysis and interpretation at the watershed scale.

**Table 2.** Accuracy Assesment in the Petung Watershed

| Period | Kappa Coefficient | |
|---|---|---|
| | K | Interpretation |
| 2005 | 0.701 | Substantial |
| 2009 | 0.782 | Substantial |
| 2014 | 0.829 | Almost Perfect |
| 2019 | 0.787 | Substantial |
| 2024 | 0.829 | Almost Perfect |

Table 2 presents the Kappa coefficient values obtained for land use classification in the Petung Watershed across the five observation years, indicating consistently acceptable to very high classification reliability. The Kappa values range from 0.701 to 0.829, corresponding to "Substantial" agreement in 2005, 2009, and 2019, and "Almost Perfect" agreement in 2014 and 2024. The lowest Kappa value was observed in 2005 (K = 0.701), suggesting that classification uncertainty was relatively higher during the earlier period, potentially due to sensor limitations and landscape heterogeneity. In contrast, higher Kappa values in 2014 and 2024 (K = 0.829) indicate improved thematic consistency and stronger agreement between classified maps and reference data, reflecting enhanced image quality and more stable classification performance in later years. Overall, the results demonstrate that all classified land use maps meet acceptable reliability thresholds for land use change analysis at the watershed scale, as Kappa values exceeding 0.70 are widely considered sufficient for thematic mapping applications. The interpretation of Kappa in conjunction with confusion-matrix–based accuracy measures follows established land cover validation practices, where Kappa serves as a conservative reliability indicator by accounting for random agreement (Gunathilaka et al., 2022), while class-specific errors can be further examined through user's and producer's accuracy to identify dominant sources of Rwanga et al. (2017).

*Spatiotemporal Dynamics of Land Use Change in the Petung Watershed*

Figure 3 and Table 3 are illustrate the spatiotemporal dynamics of land use change in the Petung Watershed from 2005 to 2024, revealing clear shifts in land use composition and spatial distribution over time. Vegetation, which dominated the watershed in 2005 with an area of 74.392 km² (52%), shows a continuous decline to 53.513 km² (38%) in 2024, indicating progressive reduction of natural cover. In contrast, agricultural land exhibits an overall increasing trend, expanding from 27.194 km² (19%) in 2005 to 49.286 km² (35%) in 2024, suggesting intensified land conversion toward productive uses. Built-up areas also increase substantially, nearly doubling from 10.711 km² (8%) in 2005 to 23.011 km² (16%) in 2024, reflecting growing anthropogenic pressure within the watershed. Bare land shows a decreasing trend after 2005, while water bodies remain relatively stable with negligible areal change throughout the study period. Spatially, these changes are characterized by expansion of built-up and agricultural land toward areas previously dominated by vegetation, particularly in accessible and transitional zones of the watershed. The observed patterns are consistent with land use change processes reported in watershed-scale studies using multi-temporal Landsat data, where vegetation loss and agricultural and urban expansion represent dominant long-term trajectories (Saraf et al., 2024).

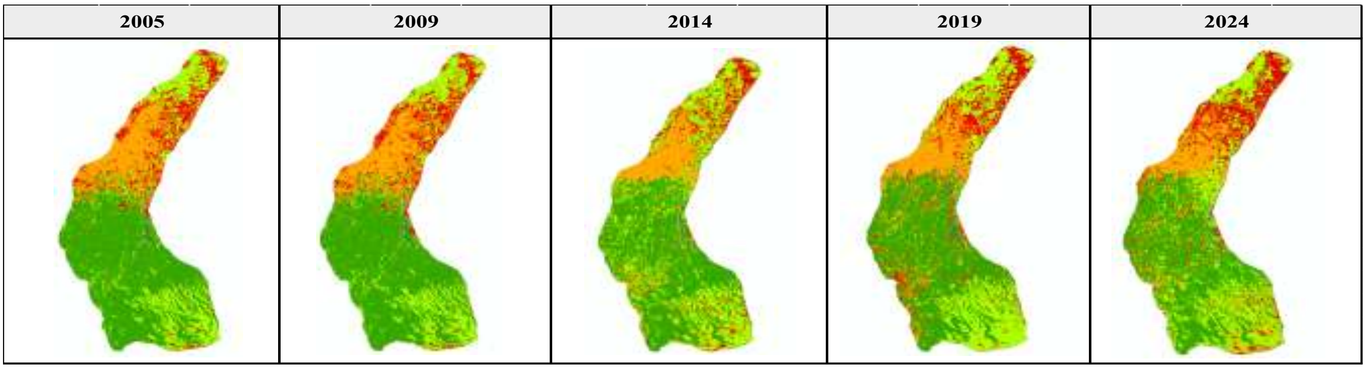


**Figure 4.** Land use change analysis in the petung watershed

**Table 3.** Distribution and area of land use classes in the Petung Watershed (2005–2024)

| Classification | 2005 | | 2009 | | 2014 | | 2019 | | 2024 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Water Bodies | 0.594 | 0% | 0.565 | 0% | 0.584 | 0% | 0.575 | 0% | 0.504 | 0% |
| Bare Land | 28.861 | 20% | 23.841 | 17% | 19.679 | 14% | 23.364 | 16% | 15.421 | 11% |
| Vegetation | 74.392 | 52% | 70.672 | 50% | 61.323 | 43% | 58.896 | 42% | 53.513 | 38% |
| Agricultural Land | 27.194 | 19% | 31.044 | 22% | 46.246 | 33% | 40.274 | 28% | 49.286 | 35% |
| Built-up Area | 10.711 | 8% | 15.628 | 11% | 13.902 | 10% | 18.619 | 13% | 23.011 | 16% |
| | 141.75 | 100% | 141.75 | 100% | 141.73 | 100% | 141.73 | 100% | 141.73 | 100% |

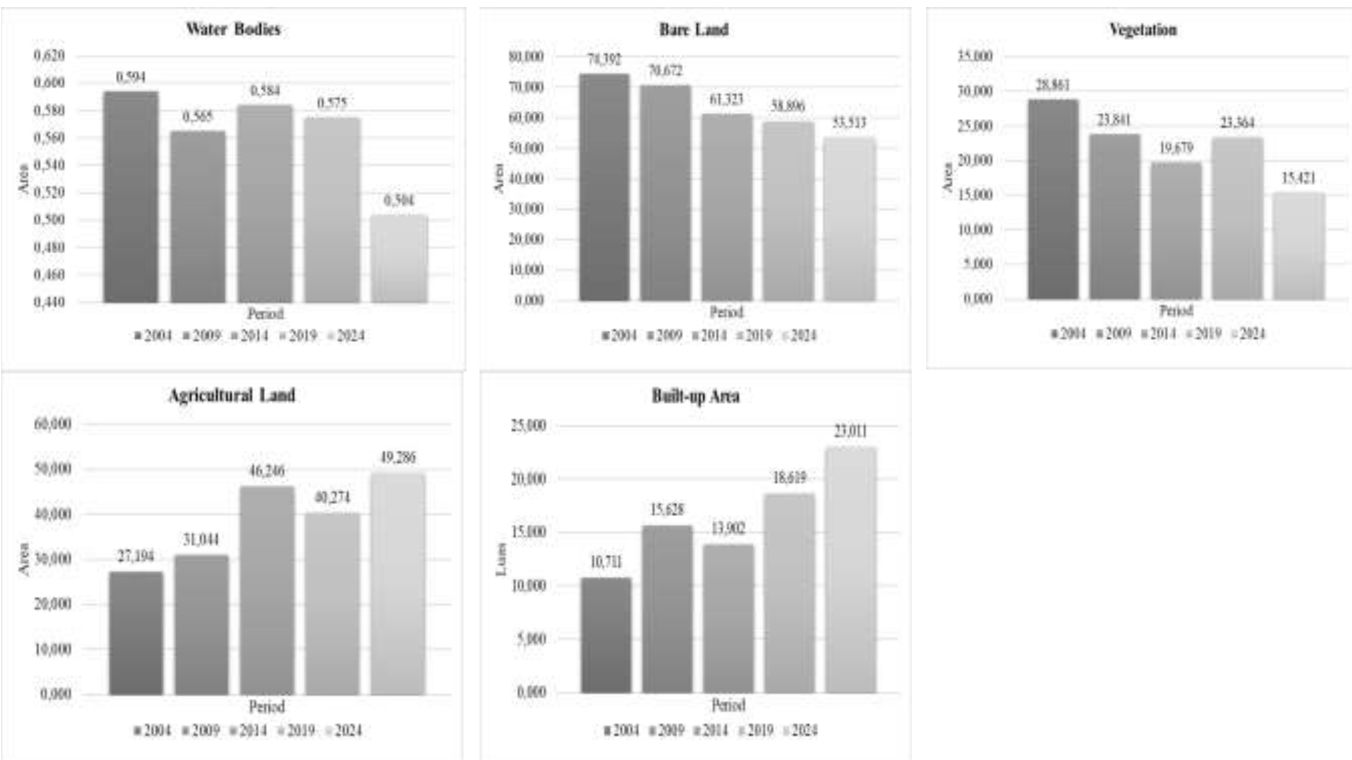


**Figure 5.** Graph of land use change in petung watershed

Figure 5 illustrates the temporal trends of land use change in the Petung Watershed from 2005 to 2024. Water bodies show relatively stable conditions throughout the observation period, indicating minimal change in surface water extent. In contrast, bare land and vegetation exhibit a general decreasing trend over time, reflecting a gradual reduction of natural and semi-natural land cover. Conversely, agricultural land demonstrates a clear increasing trend, suggesting ongoing land conversion toward productive uses. Built-up areas also show a consistent expansion across the study period, indicating increasing anthropogenic activities within the watershed. Overall, the graphical patterns reveal a dominant shift from vegetated and open land toward agricultural and built-up land uses, highlighting the progressive transformation of land use in the Petung Watershed.

## Conclusion

This study aimed to analyze the spatiotemporal dynamics of land use change in the Petung Watershed from 2005 to 2024 using multi-temporal Landsat imagery and a supervised classification approach. More importantly, the results confirm that the GIS-based supervised classification framework calibrated using the Kappa Coefficient provides a reliable and consistent approach for assessing long-term land use change at the watershed scale. The results indicate a clear and consistent transformation of land use, characterized by a substantial decline in vegetation cover alongside a pronounced expansion of agricultural and built-up areas. Vegetation, which initially dominated the watershed, decreased progressively over the study period, while agricultural land increased markedly and built-up areas nearly doubled, reflecting intensifying anthropogenic pressure. The reliability of the classification results is supported by Kappa coefficient values ranging from 0.701 to 0.829, corresponding to “Substantial” to “Almost Perfect” agreement, with higher accuracy achieved in later years, indicating improved thematic consistency across multi-temporal datasets. The higher accuracy achieved in the more recent observation years indicates improved thematic consistency, reflecting better image quality from Landsat 8 and 9 as well as more stable processing performance. These findings confirm that the applied supervised classification framework is effective for capturing long-term land use dynamics at the watershed scale. Variations in land use patterns across the observation periods highlight the sensitivity of land use change analysis to temporal resolution and classification consistency, emphasizing the importance of standardized image pre-processing and accuracy calibration when integrating multi-sensor Landsat data. Despite the robust results, this study is limited by the moderate spatial resolution of Landsat imagery and the reliance on visual interpretation–based reference data; therefore, future research is recommended to incorporate higher-resolution imagery, additional classification techniques, and quantitative linkage with hydrological or environmental indicators to further enhance land use change assessment. Future studies are recommended to utilize higher-resolution satellite imagery and integrate land use change data with hydrological or environmental indicators to further strengthen watershed management analysis.

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**Author Contributions**

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**Conflicts of Interest**

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted independently without any commercial or financial relationships that could be construed as a potential conflict of interest, and the findings presented reflect the objective results of the study.

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