Analysis of Urban Changes Using Multi-Temporal Satellite Data in Buriram Province, Thailand

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Abstract
Land use dynamics are evident and closely linked to changes in population, economy, and society. In Southeast Asian secondary cities, rapid urbanization driven by tourism and economic diversification presents complex spatial transformations that require systematic monitoring. Buriram Province, Thailand, exemplifies this phenomenon, having transformed from an agriculture-dependent economy to a sports tourism destination, with tourism revenue reaching 4,859.91 million baht in 2019. Despite this dramatic transformation, comprehensive spatial-temporal analysis of land use changes using advanced machine learning approaches remains limited for secondary cities in developing countries, creating a critical knowledge gap for evidence-based urban planning. This study addresses this gap by leveraging the Google Earth Engine platform to collect Landsat satellite data and employs machine learning, specifically Random Forest classification, to monitor land use dynamics, urban expansion, and construction activities in Buriram Province over the years 2001, 2011, and 2021. The findings reveal notable changes in land use within Buriram Province, categorized into growth-oriented and decline-oriented transformations. Growth-oriented changes include expansion of community areas and construction sites totaling 717.76 km², and water source areas increasing by 160.94 km². Decline-oriented changes comprise agricultural land decreasing by 606.33 km², forest areas declining by 235.04 km², and miscellaneous areas declining by 37.33 km². Over the 21 years from 2001 to 2021, urban and construction areas expanded by 717.76 km². The districts experiencing the most significant increases in urban areas include Muang Buriram District, Nang Rong District, and Prakhon Chai District, with respective increases of 90.44 km², 82.97 km², and 60.57 km². Furthermore, Chaloem Phra Kiat District, Nong Hong District, and Phlapphla Chai District exhibited the highest relative urban growth rates, with urban areas increasing by 245%, 222%, and 197% from their 2001 baseline areas, respectively, over the 21-year period.

Keywords: Multi-Temporal, Satellite Data, Urban Changes

1. Introduction

The transformation of land use in each area is dynamic and influenced by economic status, societal factors, and population dynamics [1] and [2]. Urban expansion often results from population growth and economic development [3]. While urban growth brings opportunities for economic development and improved quality of life, it also leads to negative impacts such as traffic congestion and population density [4], as well as a decrease in agricultural land, affecting food security [5]. Monitoring changes in land use is integral to understanding global changes that affect environmental balance and human existence [6]. Over the past years, land use in Thailand has undergone rapid changes due to population growth and economic and industrial expansion, resulting in increased utilization of natural resources. Comparing population figures in Thailand, there has been an increase from 62,308,887 in 2001 to 66,090,475 in 2022 [7], indicating a population growth of 3,781,588 or an average annual increase of 180,075 people, equivalent to 5.72%. With this population growth, the demand for land use has also risen. Limited available land has led to significant shifts in land use patterns, resulting in environmental degradation and affecting livelihoods in various ways, such as the expansion of residential areas, depletion of forest resources, reduction of agricultural land, and proliferation of industrial facilities. Efforts have been made to comprehend these phenomena through the application of techniques and methodologies in studying land use change models [8]. Past and present land use data are crucial for future land use planning.

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Buriram province, with a population of 1,576,915 people [9], ranks 7th in the country. From 2001 to 2022, there was an increase of 43,041 people, representing a growth rate of 2.73%. Once a small town, it has now evolved into a secondary city, shifting towards tourism development. Sports and tourism serve as models for development, with facilities such as the Chang Arena football stadium, boasting a capacity of 32,600 seats [10], and the international standard racing track, Chang International Circuit [11]. Buriram is a province renowned for its historical significance and boasting the most volcanic tourist destinations in the country, including six mountains: Khao Phanom Rung, Khao Angkhan, Khao Prapadaeng, Khao Lueb, Khao Krabdong, and Khao Khok [12]. In 2021, tourist numbers reached 758,081 [13], prompting investments in hotels and restaurants, thereby creating employment opportunities and income. Consequently, Buriram has transformed into a "sports tourism city" renowned throughout Asia [14].

The classification of land use, facilitated by satellite data, has become crucial in studying land use changes [15]. Landsat satellite imagery is freely available through cloud-based platforms like Google Earth Engine, enabling diverse applications, particularly in tracking changes in land use over time [16][17] and [18]. Satellite data is employed in conjunction with unsupervised and supervised classification methods. Supervised classification methods necessitate the creation of training dataset samples to train the classifier [19]. Among supervised classification methods, the maximum likelihood (MLC) method is commonly utilized due to its accuracy and popularity [20]. However, challenges arise in the accuracy of classification results due to noise interference and the requirement for normally distributed training dataset samples [21]. Machine learning algorithms have been developed to enhance the accuracy and efficiency of satellite data classification, with applications in land use classification [22] and vegetation classification [23]. Among supervised classification methods, the Random Forest algorithm has demonstrated superior performance in land use classification tasks [24]. This ensemble learning approach combines multiple decision trees to provide several key advantages for remote sensing applications: robustness to noise in satellite imagery, efficient handling of large multi-temporal datasets, and provision of feature importance rankings that enhance interpretability [21]. The algorithm's capacity to manage high-dimensional spectral data while avoiding overfitting makes it particularly well-suited for satellite-based land use classification [25]. Additionally, Random Forest effectively handles the mixed data types and temporal variations commonly encountered in multi-temporal satellite analysis, providing classification confidence estimates essential for change detection studies. Therefore, this study implements the Random Forest algorithm within the GEE framework to analyze multi-temporal land use changes in Buriram Province from 2001 to 2021, enabling comprehensive monitoring of urban expansion patterns.

The development of models and techniques to simulate urban expansion and land use change under different scenarios is crucial for urban planners and policymakers to understand the potential future expansion of cities [5]. Currently, various models and techniques have been developed to work in conjunction with remote sensing technology and geographic information systems for simulating urban expansion patterns and modeling changes in land use and land cover. Researchers have studied spatial and temporal changes in land use and land cover. For example, land use and land cover changes using Landsat satellite data in the Ganges River basin, Uttar Pradesh, India [26]. Mapping of land use changes in Vietnam using Landsat satellite data [27]. Landsat satellite data was used to track changes in land use and land cover in Pathumthani province, Thailand [28].

Therefore, this study highlights the economic transformation of Buriram province, which has experienced rapid economic growth. The Gross Provincial Product (GPP) in 2021 amounted to 84,763 million baht, indicating a trend of changes in land use, including urban expansion, agricultural activities, tourism, and potential issues arising from inappropriate land use, such as uncontrolled urban sprawl and encroachment on conservation areas. Researchers utilized the GEE platform, which integrates satellite imagery from various sources and algorithms to classify land use types. The objective of this research is to analyze changes in land use and urban expansion in 2001, 2011, and 2021, providing a database for relevant agencies to plan appropriate land use in the future context of the area.

2. Study Area

Buriram Province is located in the northeastern region of Thailand, with coordinates in Universal Transverse Mercator *(*UTM*)* Zone 48P ranging from 219,408 meters to 343,454 meters east and from 1,560,530 meters to 1,749,994 meters north. (Figure 1) The province has a population of 1,576,915 people, ranking 7^{th} in Thailand. It covers a total area of 10,066.99 km^2 and is divided into 23 districts.

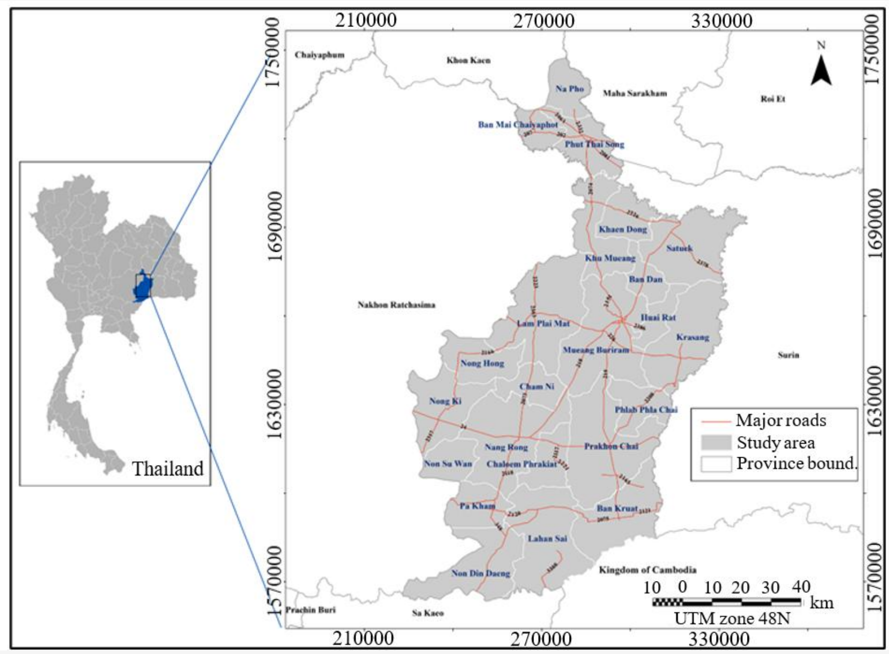

Figure 1: Buriram province, Thailand

Table 1: Satellite data

Satellite	Data			
	Resolution(m)	**Data Type**	**Band/Mod**	**Acquisition**
Landsat-5 TM	30	BOA Surface Reflectance	Band 4 (near infrared) surface reflectance Band 3 (red) surface reflectance Band 2 (green) surface reflectance	January 2001, 2011
Landsat-8 OLI	30	BOA Surface Reflectance	Band 5 (near infrared) Band 4 (red) surface reflectance Band 3 (green) surface reflectance	January 2021

Buriram's agricultural area spans 7,304.12 km^2, accounting for 70.76% of the total land area. This includes 4,784.52 km^2 for rice cultivation, 1,276.57 km^2 for field crops, and 1,243.02 km^2 for fruit crops. Additionally, the province features 416.59 km^2 of irrigated land, which represents 20.85% of the agricultural area. The GPP of Buriram is valued at 92,023 million Baht, with the agriculture, forestry, and fisheries sector contributing 21,278 million Baht. The manufacturing sector follows with 14,060 million Baht, and the wholesale, retail, and motor vehicle repair sectors contribute 12,422 million Baht [9].

3. Data and Methodology

3.1 Data Used

This study employed satellite data from Landsat-5 TM and Landsat-8 OLI encompassing Buriram province. The designated paths and rows were Path*:* 127, 128, and Row*:* 049, 050. The dataset extended from 2001 to 2021 and was accessed via GEE.

3.2 Methodology

GEE, a cloud-based geospatial platform, facilitates the analysis of spatial data pertaining to the Earth's surface. Leveraging server-side computing capabilities, it expedites the processing of satellite imagery, enabling seamless handling of data from various satellite sources. Moreover, GEE is adept at managing large-scale data processing tasks and offers algorithms for precise and automated land use classification within the designated study area [29]. Land use data classification is executed via the Code Editor using JavaScript, allowing access to satellite imagery data from 2001, 2011, and 2021. Subsequently, the data undergoes processing and interpretation to classify land use and land cover, employing supervised classification, particularly the Random Forest method. Accuracy assessment and analysis of land use change are carried out through a Confusion Matrix. The study process is delineated as illustrated in Figure 2.

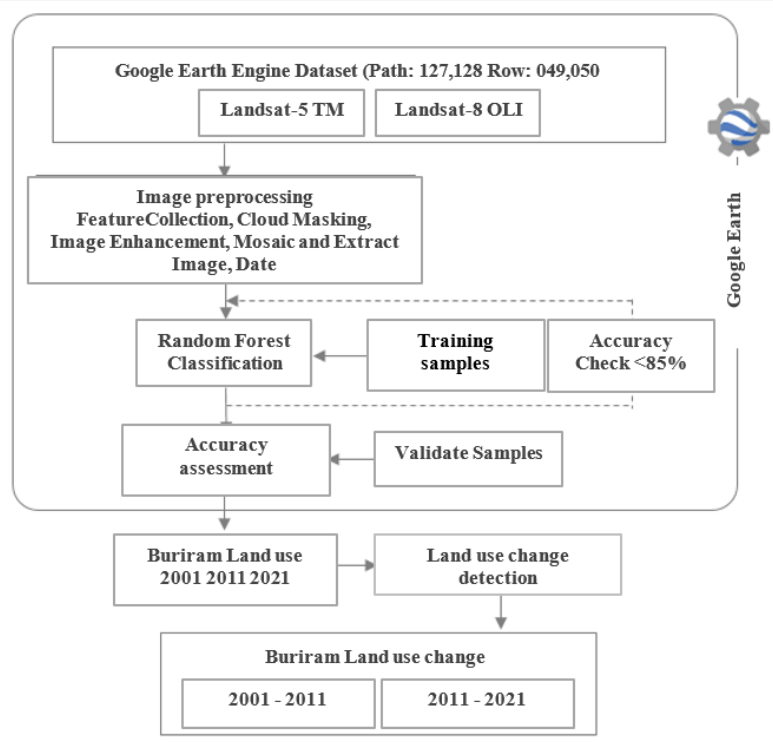

Figure 2: The research methodology

Preliminary processing involves the following steps. Satellite data from Landsat-5 TM (2001 and 2011) and Landsat-8 OLI (2021), featuring a pixel resolution of 30 meters, is accessible for download from the cloud platform in GEE via the Image Collection Function. Following this, the Filter Function is applied to the satellite data to refine it based on the specified time range, employing the Date function.

1) Import vector boundary data of Buriram province to access open vector data.
2) Apply a filtering function to select the time range, considering the day, month, and year of the satellite data used in the study, specifically targeting 2001, 2011, and 2021.
3) Utilize cloud masking techniques, leveraging the cloud filter function in GEE, to mitigate the impact of cloud cover when analyzing satellite time series data. This ensures obtaining cloud-shadow-free data for accurate analysis.
4) Implement image enhancement techniques to adjust the color levels of image pixels, enhancing details and clarity for improved interpretation of land use and land cover types. Methods like layer stacking or band combination are commonly used for this purpose.
5) Mosaic and extract images in Buriram Province by merging multiple scenes and selecting only the relevant area within the province to focus on the study area effectively.

In this study, land use was classified into five categories*:* Urban and Built-up, Agriculture, Forest, Water, and Miscellaneous. This classification aligns with the Level 1 land use categorization system of the Land Development Department the classification of land use and land cover types, the process begins with the creation of a training dataset using a geometry creation tool. The training data is represented as a FeatureCollection, containing properties to store class labels and predictor variables. Class labels are assigned as consecutive integers, starting from 0. In this specific scenario, a training dataset for five land use categories was generated using Taro Yamane's formula, with a 95% confidence level and a maximum margin of error of 5%, comprising a total of 400 points distributed across the five land use categories. The Supervised Classification method is employed, specifically utilizing the Random Forest algorithm.

The accuracy assessment for land use classification in the years 2001 and 2011 utilized land use data from the Department of Land Development. For the year 2021, field surveys were conducted,

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employing the Confusion Matrix method to validate land use categories. To ensure robustness, validation points for each land use category and year were randomly selected, comprising at least 30% of the total sample points. The overall accuracy (Equation 1) and Kappa Index (Equation 2) were calculated to evaluate the classification's accuracy. The minimum acceptable accuracy threshold was set at 80% [30].

$$OA = \frac{\sum_{r=1}^{i} n_{ii}}{N}$$

Equation 1

Where:

OA = Overall Accuracy,
i = Number of rows in the Confusion Matrix,
n_{ii} = Value in row i and column i,
N = Total number of validation points

$$K = \frac{N\sum_{r=1}^{i} n_{ii} - \sum_{r=1}^{i}(n_{i+} \cdot n_{+i})}{n^2 - \sum_{r=1}^{i}(n_{i+} \cdot n_{n+1})}$$

Equation 2

Where:

K = Kappa coefficient,
N = Total number of validation points in the Confusion Matrix,
r = Number of rows in the Confusion Matrix,
n_{ii} = Value in row i and column i,
n_{+i} = Sum of reference values in each column i,
n_{i+} = Sum of reference values in each row i

3.3 Land Use Changes

To analyze the changes in land use for the years 2001, 2011, and 2021, a comparison of land use can be conducted to examine these changes. This table will assist in assessing overlaps between different land use categories and identifying changes during two specific periods: Period 1, between 2001 and 2011, and Period 2, between 2011 and 2021 [31].

4. Results and Discussion

The changes in land use, utilizing data from multiple time periods and satellite imagery, facilitate the classification of land use and land cover in Buriram Province. Using satellite data from Landsat-5 TM and Landsat-8 OLI for the years 2001, 2011, and 2021, the classification results for all three years reveal the proportions of land use as follows:

In 2001, the land use accuracy was 92.68%, with a Kappa coefficient of 0.91. The land was utilized as follows: agricultural land covered 8,308.42 km^2, forest area covered 1,198.22 km^2, urban and built-up areas covered 351.32 km^2, water sources covered 147.87 km^2, and miscellaneous areas covered 61.15 km^2. These areas accounted for the following proportions of the total area: agricultural land (82.53%), forest area (11.90%), urban and built-up areas (3.49%), water sources (1.47%), and miscellaneous areas (0.61%), as depicted in Figure 3.

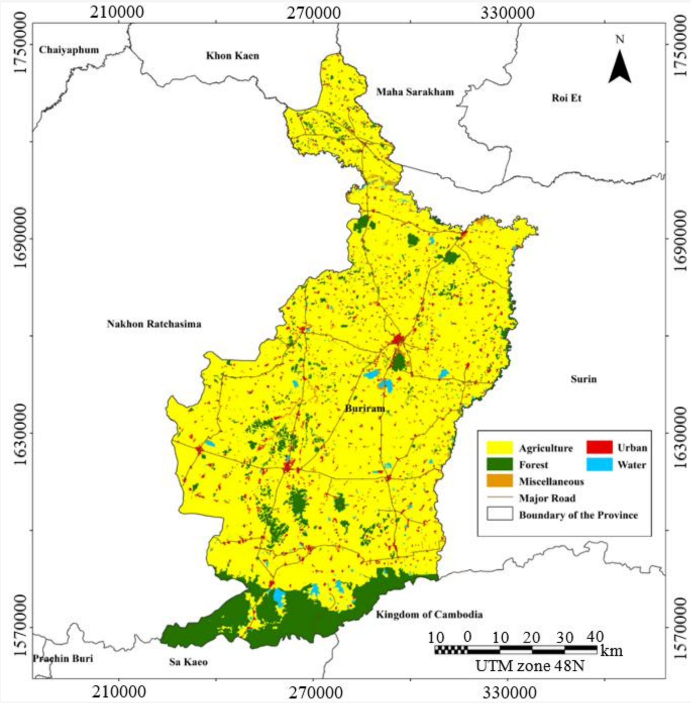

Figure 3: Land Use in Buriram Province from the Year 2001

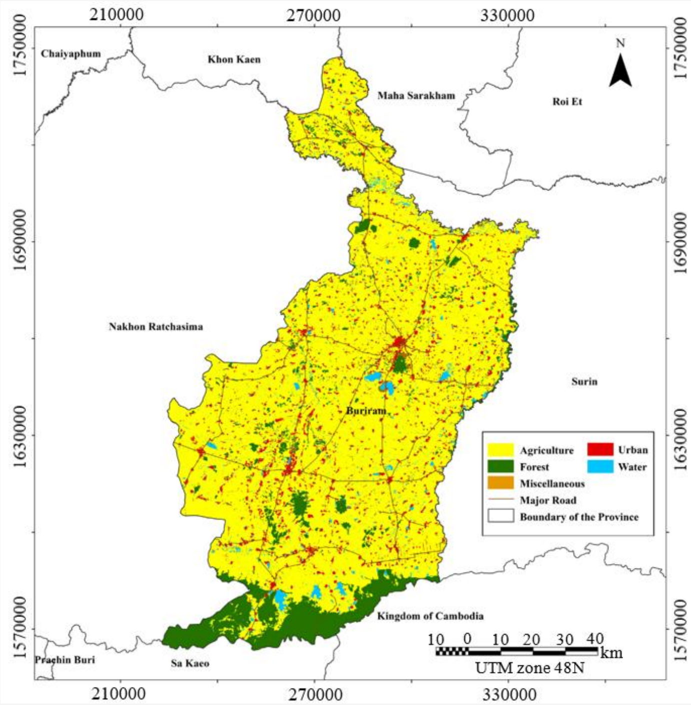

Figure 4: Land Use in Buriram Province from the Year 2011

In 2011, the land use accuracy was 88.43%, with a Kappa coefficient of 0.86. The land was utilized as follows: agricultural land covered 8,096.22 km^2, forest area covered 1,029.03 km^2, urban and built-up areas covered 580.40 km^2, water sources covered 293.18 km^2, and miscellaneous areas covered 68.15 km^2. These areas accounted for the following proportions of the total area: agricultural land (80.42%), forest area (10.22%), urban and built-up areas (5.77%), water sources (2.91%), and miscellaneous areas (0.68%) as depicted in Figure 4.

In 2021, the overall accuracy of land use was 93.17%, with a Kappa coefficient of 0.92. The land was utilized as follows: agricultural land covered an area of 7,702.10 km^2, forest areas covered 963.18 km^2, urban and built-up areas occupied 1,069.08 km^2, water sources spanned 308.81 km^2, and miscellaneous areas accounted for 23.82 km^2. These areas accounted for the following proportions of the total area: agricultural land (76.51%), forest area (9.57%), urban and built-up areas (10.62%), water sources (3.07%), and miscellaneous areas (0.24%), as depicted in Figure 5.

Between 2001 and 2021, the most significant increase in land use change was observed in urban and built-up areas, totaling 229.09 km^2. Following that, water sources and miscellaneous areas also had an increase of 145.31 and 7 km^2, respectively. Conversely, there was a decrease in agricultural land use by 212.20 km^2 and forest areas by 169.19 km^2. These findings are summarized in Table 2 and as depicted in Figure 6. Land use changes between 2011 and 2021 reveal that urban and built-up areas had the highest increase, totaling 488.67 km^2. Following this, water sources increased by 15.64 km^2. Conversely, there were decreases in agricultural areas amounting to 394.13 km^2. Additionally, decreases were observed in forest areas and miscellaneous areas, amounting to 65.85 and 44.33 km^2, respectively. This information is summarized in Table 3 and depicted in Figure 7.

Between 2001 and 2021, significant changes in land use have occurred in Buriram Province. The most notable change is the expansion of urban and built-up areas, which increased by 717.76 km^2, representing 40.84% of the total change. Conversely, there was a decrease in agricultural areas, which contracted by 606.33 km^2, accounting for 34.50% of the total change. Additionally, forest areas decreased by 235 km^2, constituting 13.37% of the change, while water source areas increased by 160.94 km^2, comprising 9.16%. Lastly, miscellaneous areas had a decrease of 37.33 km^2, representing 2.12% of the total change. These findings are illustrated in Figure 8.

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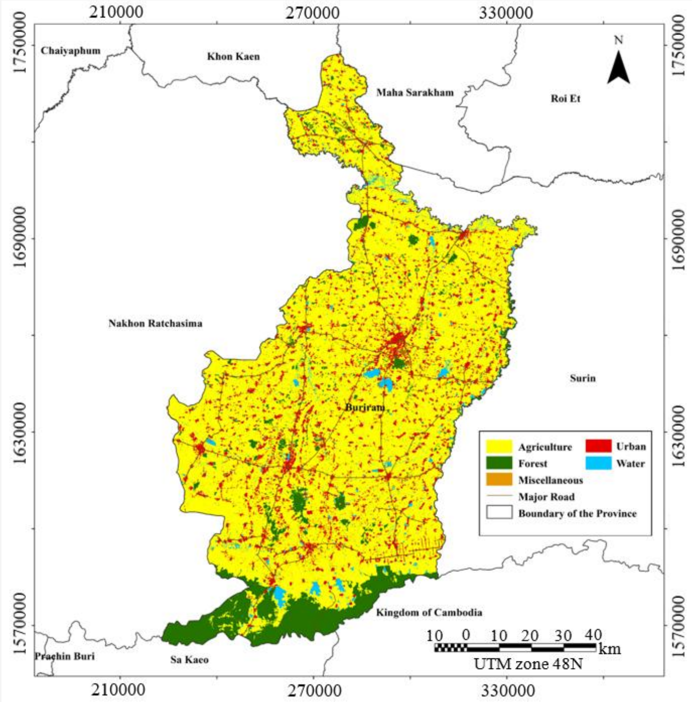

Figure 5: Land Use in Buriram Province from the Year 2021

Table 2: Land Use changes between the Years 2001 and 2011

	Land Use	**Land Use 2011**					**Total Area**
		Agriculture	**Forest**	**Miscellaneous**	**Urban**	**Water**	**(km^2)**
Land use 2001	Agriculture	7,916.59	0	24.98	219.84	147.00	8,308.42
	Forest	154.02	1,029.03	8.74	6.44	0	1,198.22
	Miscellaneous	25.62	0	22.85	2.81	9.88	61.15
	Urban	0	0	0	351.32	0	351.32
	Water	0	0	11.58		136.30	147.87
	Total area (km^2)	8,096.22	1,029.03	68.15	580.40	293.18	10,066.99
	Changed area (km^2)	-212.20	-169.19	7.00	229.09	145.31	
	Changed area (%)	-2.11	-1.68	0.07	2.28	1.44	
	Rate of change per year (km^2)	-21.22-	-16.92	0.70	22.91	14.53	

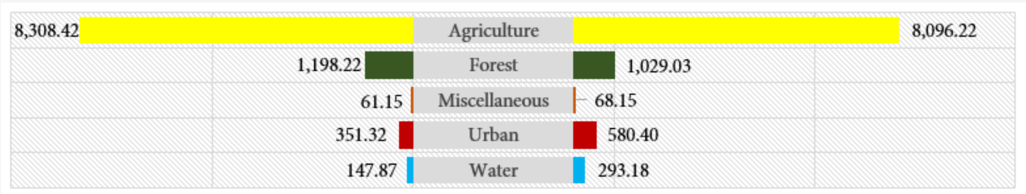

Figure 6: Comparison of Land Use 2001 and 2011 (unit in km^2)

Table 3: Land Use changes between the Years 2011 and 2021

	Land Use	**Land use 2021**					**Total Area**
		Agriculture	**Forest**	**Miscellaneous**	**Urban**	**Water**	**(km^2)**
Land use 2011	Agriculture	7,626.75	0	2.11	467.36	0	8,096.22
	Forest	59.05	960.56	0	7.90	1.53	1,029.03
	Miscellaneous	16.30	2.62	21.49	13.42	14.33	68.15
	Urban	0	0	0	580.40	0	580.40
	Water	0	0	0.22		292.96	293.18
	Total area (km^2)	7,702.10	963.18	23.82	1,069.08	308.81	10,066.99
	Changed area (km^2)	-394.13	-65.85	-44.33	488.67	15.64	
	Changed area (%)	-3.92	-0.65	-0.44	4.85	0.16	
	Rate of change per year (km^2)	(39.41)	(6.58)	(4.43)	48.87	1.56	

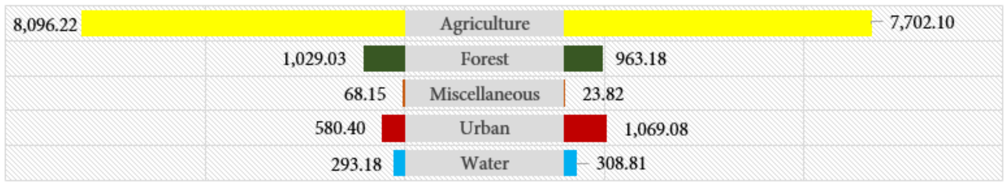

Figure 7: Comparison of Land Use 2011 and 2021 (unit in km^2)

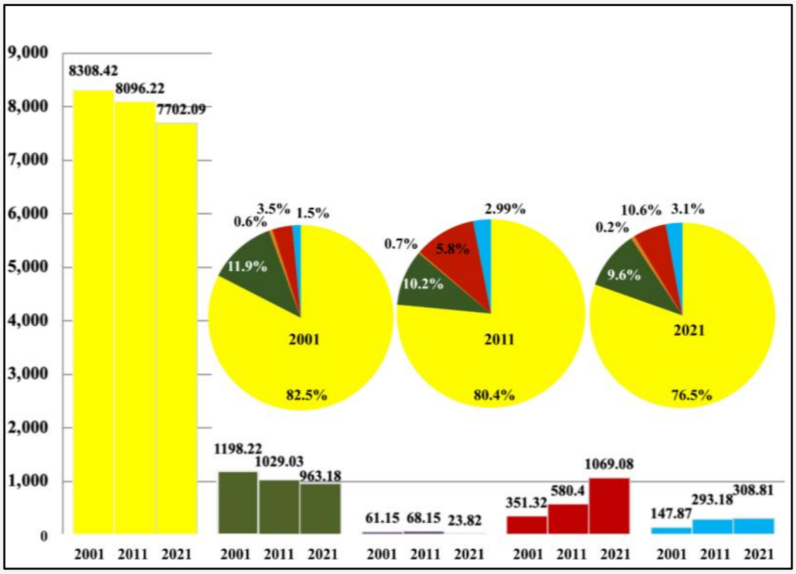

Figure 8: Comparison of Land Use between 2011 and 2021

Over the span of 21 years, from 2001 to 2021, there has been a total land use change of 1,757.40 km^2. The most notable change occurred in urban and built-up areas, which increased by 717.76 km^2. Additionally, agricultural areas decreased by 606.33 km^2, while forest areas experienced a reduction of 235.04 km^2. Conversely, water source areas had an increase of 160.94 km^2, while miscellaneous areas decreased by 37.33 km^2.

The transformation of urban and built-up structures in Buriram Province has been chiefly driven by the presence of Highway 24, also known as the Kiew-Warin Chamrap Highway, serving as the primary artery of the northeastern region. This thoroughfare spans across the provinces of Nakhon Ratchasima, Buriram, Surin, Si Sa Ket, and Ubon Ratchathani. Additionally, a railway line connects Nakhon Ratchasima to Ubon Ratchathani. The expansion of residential areas has manifested in clustered settlements [32]. Predominantly, significant urban development is concentrated in the central zones of Nang Rong, Prakhon Chai, Lam Plai Mat, and Nong Ki districts, adjacent to national highways that play pivotal roles in transportation, commerce, and services. Notably, there is an observable elongated urban sprawl along transportation corridors linking Nong Ki, Nang Rong, and Prakhon Chai, situated along the Provincial Highway connecting these districts on the northeastern region's main route. Furthermore, a proliferation of residential houses, building expansions, planned villages, and shopping malls has been witnessed along the road connecting Muang Buriram District to Nang Rong District, contributing to the expansion of urban and built-up areas (Figure 9). The districts experiencing the most substantial expansion of urban and built-up areas, in descending order, are Muang Buriram District with 90.44 km^2, Nang Rong District with 82.97 km^2, Prakhon Chai District with 60.57 km^2, Lam Plai Mat District with 54.89 km^2, and Krasang District with 52.62 km^2, as depicted in Figure 10.

The surge in urban and built-up areas in Buriram Province stems from the province's concerted efforts to boost tourism and sports, positioning itself as a "Sports City" under the banner "City of Stone Castles, Land of Volcanoes, Beautiful Silk, Culturally Rich, and Superb Sports City." This strategic development aims to position Buriram as a premier global tourist and sports destination, leveraging iconic landmarks such as the Chang Arena football stadium, Chang International Circuit, Phanom Rung Stone Castle, Muang Tam Stone Castle, and volcanic landscapes [33].

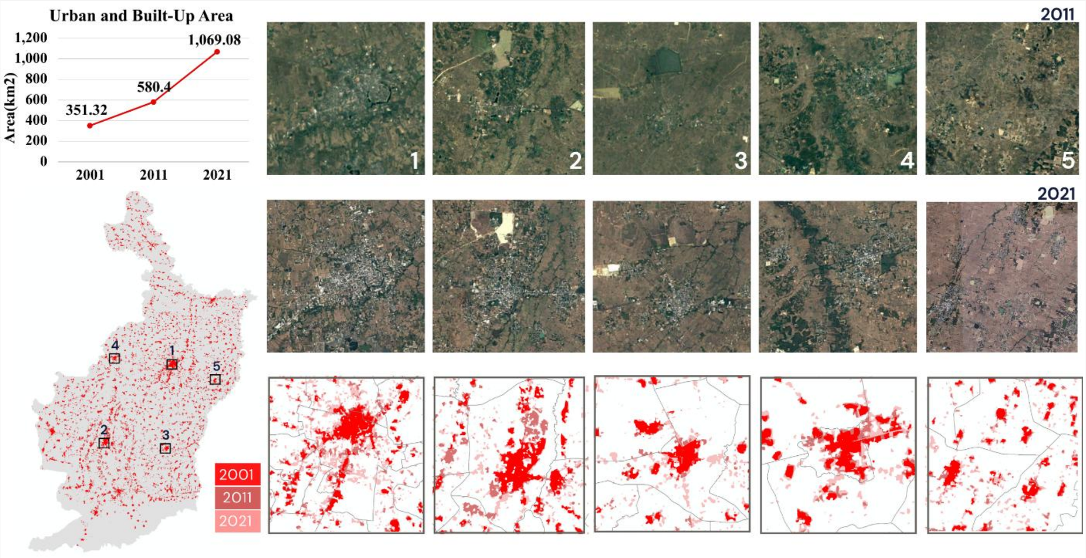

Figure 9: The urban and built-up area of Buriram Province for the Years 2001, 2011, and 2021

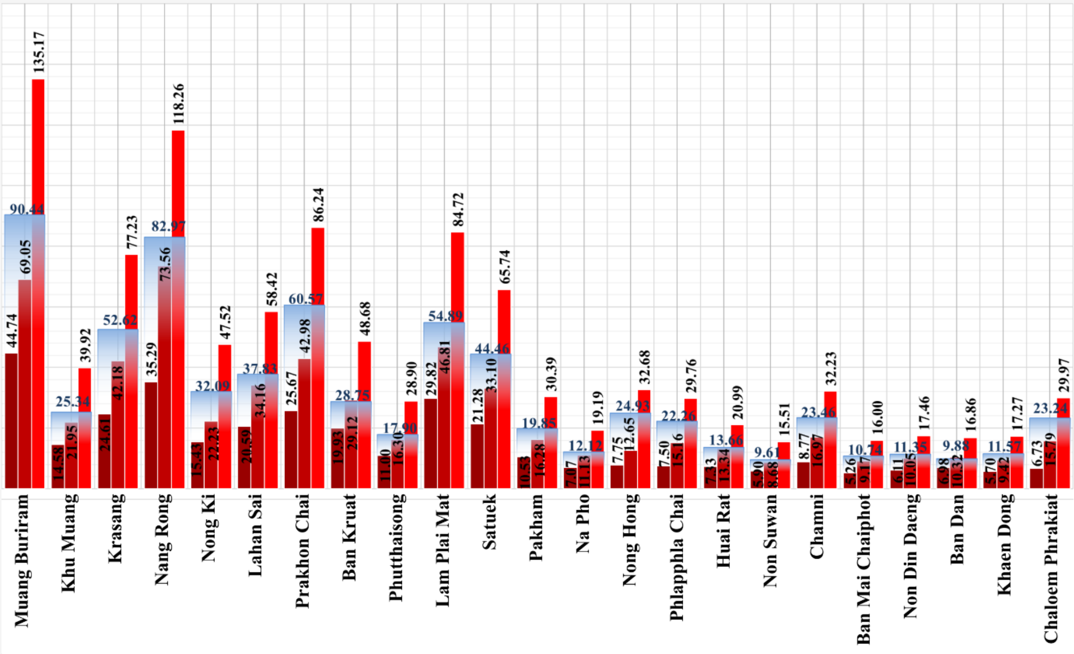

Figure 10: Comparison of the Urban and Built-Up Areas of Buriram Province in 2001, 2011, and 2021

These endeavors have garnered attention from both domestic and international tourists, reflected in a notable increase of 12.52% in tourist arrivals. Tourism revenue reached 4,859.91 million baht in 2019, with significant investments pouring in from large-scale capital groups within the service sector and retail [34]. Development initiatives across various sectors in Buriram Province have catalyzed changes in both its economic and cultural landscapes. This has propelled the province towards its development plan to establish itself as a hub for global-standard cultural and sports tourism. The plan prioritizes economic growth through the enhancement of agricultural product manufacturing, bolstering the tourism industry, and elevating the service sector [33]. These concerted efforts have resulted in Muang District experiencing the most substantial increase in urban and built-up areas. This transformation encompasses the development of residential areas, allocated housing, shopping centers, sports facilities, and government buildings, as illustrated in Figure 11.

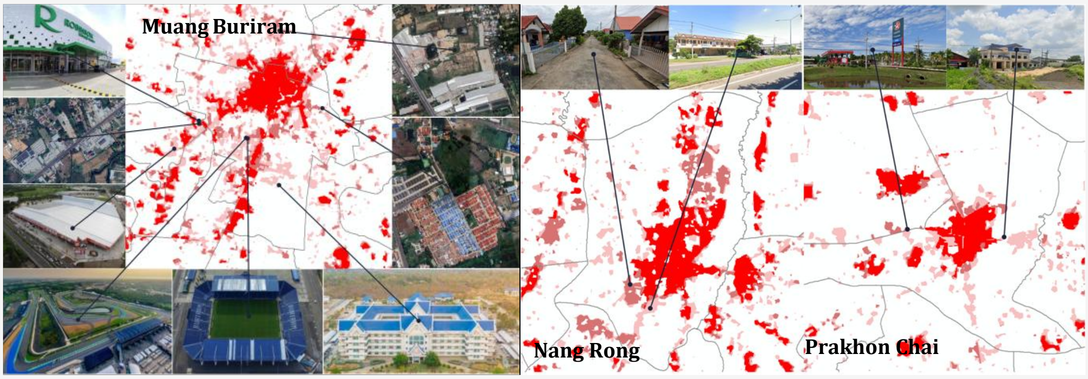

Figure 11: The increase in urban and built-up areas in Muang District, Nang Rong District, and Prakhon Chai District of Buriram Province

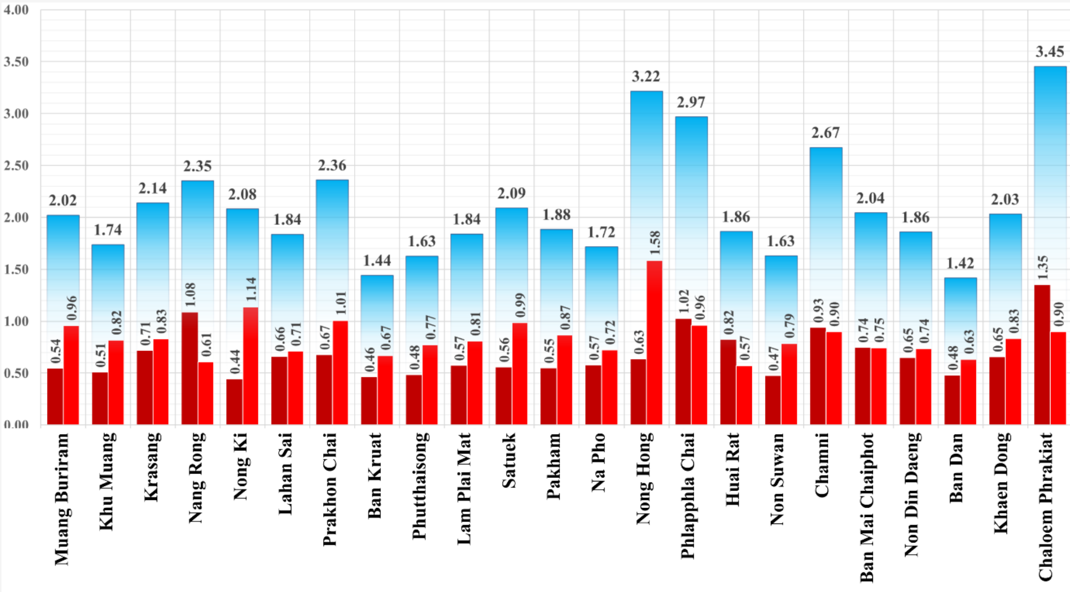

Figure 12: Urban Growth Rate in Buriram Province between 2001- 2021

The growth rate of urban and built-up areas in Buriram Province was examined from 2001 to 2011. The top three districts with the highest growth rates during this period were Chaloem Phra Kiat District, Nang Rong District, and Phlapphla Chai District, with growth rates of 1.35, 1.08, and 1.02, respectively. From 2011 to 2021, the top three districts experiencing the highest growth rates were Nang Rong District, Nong Ki District, and Prakhon Chai District, with growth rates of 1.58, 1.14, and 1.01, respectively. When considering the growth rate of urban and built-up areas in Buriram Province from 2001 to 2021, the top three districts with the highest growth rates were Chaloem Phra Kiat District, Nong Hong District, and Phlapphla Chai District, with growth rates of 3.45, 3.22, and 2.97, respectively as displayed in Figure 12.

5. Conclusion

This comprehensive analysis of land use change in Buriram Province from *2001* to *2021* reveals significant spatial-temporal transformations driven by interconnected economic and social factors. Machine learning classification using Random Forest techniques achieved high accuracy levels of *92.68%*, *88.43%*, and *93.17%* across the three study periods, with corresponding Kappa coefficients of *0.91*, *0.86*, and *0.92*, demonstrating the effectiveness of random forest scheme on image classification and satellite-based monitoring to understand land use dynamics in developing regions.

In the aspect of land use change, the most significant finding is the dramatic *40.84%* increase in urban and built-up areas, representing *717.76* km² of expansion, which coincided with substantial reductions in agricultural land (*606.33* km² or

34.50%) and forest cover (*235.04* km² or *13.37%).* This pattern reflects the province's economic transition from agriculture-dependent to service-oriented economy, with tourism and sports development emerging as primary growth drivers. Agricultural contribution to GPP decreased from *25.1%* to *18.7%* while service sectors increased to *52.3%*, demonstrating successful economic diversification. The study identified distinct spatial patterns, with Muang Buriram, Nang Rong, and Prakhon Chai districts experiencing the highest absolute increases in urban areas, while Chaloem Phra Kiat, Nong Hong, and Phlapphla Chai districts exhibited the highest relative growth rates at *3.45*, *3.22*, and *2.97* times their *2001* baseline areas, respectively. Tourism development played a catalytic role, with pre-pandemic tourist arrivals reaching 2,267,080 in 2019, generating 4,859.91 million baht in revenue [33]. Although the COVID-19 pandemic reduced arrivals to 758,081 in 2021 [13], the province's tourism infrastructure investments continued to drive urban expansion throughout the study period.

The spatial-temporal patterns and cross tabulation identified in this study provide actionable evidence for evidence-based policy development and implementation. The high classification accuracy and detailed mapping of urban expansion hotspots enable targeted policy interventions with measurable outcomes. Policy recommendations emphasize implementing Smart Growth principles through spatial prioritization strategies. These recommendations are both feasible and implementable given Buriram Province's existing institutional capacity and recent investments in tourism and sports infrastructure. Muang Buriram District should serve as the primary development hub with urban growth boundaries established around Main Sport Stadium and the city center, promoting transit-oriented development (TOD) a planning strategy that clusters mixed-use development around transit stations to reduce automobile dependency and create walkable communities, which is particularly appropriate for Buriram given its existing railway station and sports infrastructure anchors between the railway station and sports facilities to reduce automobile dependency. Expansion corridors along Highway *24* through Nang Rong and Prakhon Chai districts should be carefully managed to prevent uncontrolled sprawl while strengthening connectivity between urban centers and peripheral areas by considering the land utilization from an urban comprehensive plan. The identified growth rates and spatial patterns provide baseline metrics for monitoring policy effectiveness and adjusting strategies over time.

Conservation measures are essential for peripheral areas and remaining forest zones, including payment for ecosystem services in Dong Phayayen Forest and Mun River Basin areas to provide incentives for environmental protection. This study establishes a robust foundation for future policy development in three critical ways: first, the high-resolution land use maps serve as baseline data for long-term monitoring and adaptive management; second, the demonstrated machine learning methodology using freely available satellite data offers a replicable and cost-effective approach for continuous monitoring; and third, the findings can directly inform revisions to Buriram Province's comprehensive land use plan and serve as a model for other secondary cities facing similar urbanization pressures. Study limitations include reliance on satellite data interpretation, suggesting future research should incorporate ground-truthing data, socioeconomic surveys, and longitudinal studies extending beyond *2021* to capture post-pandemic development patterns. These findings demonstrate that secondary cities in developing countries can successfully leverage tourism and sports infrastructure for economic growth while requiring careful balance between development objectives and environmental stewardship through evidence-based planning policies.

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