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EVALUATION OF FLASH FLOOD SUSCEPTIBILITY IN RELATION TO LAND USE CHANGES IN CHIANG RAI, THAILAND

*Zhaolong Gu[1], Daisuke Komori[2] and Thapthai Chaithong[3]

[1]Graduate School of Environmental Studies, Tohoku University, Japan; [2]Green Goals Initiative, Tohoku University, Japan; [3]Faculty of Social Sciences, Kasetsart University, Thailand

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ABSTRACT: Flash floods are among the most destructive natural hazards in mountainous regions, characterized by their rapid onset and severe impact on lives and infrastructure. This study assessed the spatio-temporal evolution of flash flood susceptibility in Chiang Rai Province, Thailand, by integrating remote sensing, Geographic Information Systems (GIS), and hydrological modeling. Using the Flash Flood Potential Index (FFPI), the study analyzed the impact of land use and land cover (LULC) changes on flood risk across three distinct periods: 2007, 2012, and 2018. The model incorporated terrain slope, soil hydrological groups (derived from HYSOGs-250m), land use, and Curve Number (CN) values to generate comprehensive risk susceptibility maps. The results revealed that the entire province falls within Moderate to High-risk categories, with a complete absence of Low-risk zones. A significant shift in susceptibility was observed over the study period, driven primarily by land-use transitions. While the conversion of woodland to agriculture moderately elevated risk levels between 2007 and 2012, the subsequent rapid urbanization of agricultural lands (2012–2018) led to a drastic escalation in vulnerability. Notably, high-risk zones within urban areas increased fivefold (+500%) during this latter period. The FFPI model was validated based on the historical flash flood records from 2019 to 2023, demonstrating a strong spatial correlation between analyzed high-risk areas and actual flash flood occurrences. These findings underscored that anthropogenic land-use changes, particularly uncontrolled urbanization and deforestation, are the primary accelerators of flash flood potential, necessitating rigorous land-use planning and targeted flood-control infrastructure.

Keywords: Flash flood, Urbanization, Land use change, GIS, Flash Flood Potential Index, FFPI

1. INTRODUCTION

Flash floods are sudden inundations triggered by short duration, high intensity rainfall events and, because of their rapid onset and unpredictability, are considered among the most destructive hydrological hazards worldwide [1]. They typically occur within minutes to a few hours after rainfall cessation, inundating normally dry areas and posing severe threats to life and property. In recent years, climate change has intensified both the frequency and magnitude of extreme precipitation, while urbanization and deforestation have diminished natural water-retention capacity and increased surface runoff, further amplifying flash flood risk [2]. Northern Thailand exemplifies these challenges: Chiang Rai Province, situated in the mountainous, monsoonal upper Mekong basin, experiences intense rainfall from May to October that frequently produces riverine flooding and flash floods with very limited warning time [3]. Conventional reliance on river gauges and rain-gauge networks is inadequate in such sparsely instrumented mountainous terrain, often leaving authorities unprepared for upstream flood peaks. This deficiency in monitoring reveals the limitations of traditional approaches. Existing flood risk assessment paradigms primarily rely on statistical records of historical inundation depth and duration to delineate hazard zones, a method that is largely inapplicable to flash floods. As noted by Borga et al. (2011) and Gaume et al. (2009), the episodic nature and extremely short lag times of flash floods mean that standard monitoring networks rarely capture peak discharges in small, responsive catchments [4][4]. Furthermore, relying solely on historical flood marks often neglects the high-velocity kinetic energy characteristic of flash floods. Therefore, flash flood research urgently needs to move beyond purely statistical analyses of gauge records and shift toward morphometric and proxy-based modeling approaches [6].

To enable spatially explicit flash flood risk assessment, Smith (2003) developed the Flash Flood Potential Index (FFPI), which standardizes and weights physio-graphic factors-slope, soil type, land cover, topographic curvature, and others-within a GIS framework to generate grid-based susceptibility scores [7]. This approach has been widely applied in ungauged catchments to identify potential flash flood source areas. Numerous global and regional studies demonstrate the efficacy of integrating the concept and framework of FFPI with remote sensing and GIS data. For instance, Kourgialas and Karatzas (2011) established a comprehensive weighting methodology for river basin flood hazards in Greece, successfully validating that the integration of slope, land cover, and geological data significantly improves the identification of high-risk zones [8]. Additionally, Zaharia et al. (2017) demonstrated the effectiveness of FFPI in the Romanian's Prahova catchment, validating its ability to identify high-risk zones based on historical torrent occurrences [9]. Similarly, Youssef et al. (2011) extended the FFPI methodology to Egypt's drylands, illustrating how morphometric parameters can highlight areas with high runoff potential. These studies underscore the utility of multi-source data such as DEMs, land-cover maps, and vegetation indices in identifying flash flood hotspots [10]. Building on this, Lazar (2020) compared FFPI maps for 1989 and 2019 in Romania's Zabala catchment, revealing that deforestation markedly elevated FFPI values [11]. Likewise, Shehata (2018) evaluated the risk in the Kyushu Island and confirmed that steep, sparsely vegetated subcatchments exhibit high FFPI scores [12]. These studies underscore that multi source data such as DEMs, land-cover maps, and vegetation indices can effectively delineate flash flood hotspots.

Globally, as urbanization accelerates and ecosystems fragment, dynamically assessing how specific land use transitions (e.g., forest to agriculture, agriculture to urban) drive flash flood susceptibility has become a critical challenge in hydrology and disaster management. The conversion of permeable vegetative cover to impervious surfaces or agricultural land fundamentally alters soil hydraulic properties, attenuating infiltration capacity and reducing surface roughness. Such alterations can drastically shorten time-to-peak and amplify peak discharge volumes, particularly during high-intensity rainfall events 0. Moreover, the agricultural expansion into water catchments promotes rapid runoff generation, effectively transferring flood risk to downstream communities [14]. However, existing assessment frameworks exhibit notable limitations. While Lazar (2020) employed bi-temporal FFPI comparisons to highlight the impact of singular land use changes on runoff and flood potential, their work was limited to static two date analyses and did not directly couple multi temporal land-use changes with quantitative FFPI variation [11]. Meanwhile, Chiang Rai Province with its complex terrain, monsoonal rainfall regime, and recurring extreme floods remains without high resolution FFPI based susceptibility mapping.

2. RESEARCH SIGNIFICANCE

To address these gaps, the present study uses 2007, 2012, and 2018 satellite-derived land use data to construct corresponding FFPI raster models, performs detailed susceptibility analyses in representative Chiang Rai catchments, and introduces a dynamic "risk transition" metric-calculating the proportion of area shifting among FFPI risk categories to quantify the spatiotemporal evolution of flash flood susceptibility and inform regional flood mitigation planning and land-use management.

3. STUDY AREA

Chiang Rai province occupies the northernmost tip of Thailand, serving as a strategic frontier region sharing borders with Myanmar to the north and Laos to the east. Encompassing approximately 11,460 km^2, the province forms a vital headwater catchment of the upper Mekong River Basin. Its terrain is characterized by a complex topography of rugged mountain ranges, deeply incised river valleys, and undulating hills, with elevations rising sharply from about 400 m in the agrarian lowlands to over 2,000 m in the highest peaks. Two principal river systems-the Nam Kok and Nam Mae-drain much of the province, flowing southeastward toward the Mekong main stem [3]. The region is governed by a tropical monsoon climate, where annual precipitation in the highlands commonly exceeds 2,000 mm, with individual storm events increasingly delivering more than 100 mm of rain within 24 hours.

Despite the severity of these hydro-meteorological conditions, the Thai government's current hydrological monitoring framework remains largely confined to lowland riverine flood events, lacking systematic real-time observation for rapid-onset flash floods in highland regions [15]. This monitoring gap is particularly alarming given the escalating frequency of disasters. According to the record, Chiang Rai province recorded 78 severe flash flood events between 2019 and 2023. This high recurrence rate demonstrates that the province is not merely a passive geographical setting for hydrological research but an active hazard hotspot where the lack of spatial risk data poses an immediate threat to public safety.

The susceptibility is further compounded by land cover dynamics. Chiang Rai presents a mosaic of tropical evergreen and deciduous forests in the upper catchments, interspersed with shifting-cultivation zones and terraced agriculture on sensitive mid-slope benches. In the lower valleys, paddy fields, small-holder orchards, and expanding peri-urban developments dominate. This heterogeneous landscape, combined with steep slopes and narrow floodplains, creates highly variable surface runoff responses. As agricultural frontiers and urban fringe areas encroach upon formerly forested hill slopes and valley bottoms, the natural infiltration capacity diminishes, exacerbating flood peaks and reducing lead times for warnings [2]. Consequently, given this complex physiography, intensifying climate regime, and the documented surge in disaster frequency, Chiang Rai represents a critical case study. Applying the Flash Flood Potential Index (FFPI) here is not only methodologically ideal for identifying spatial hot spots but is also an operational necessity to understand how evolving land-use dynamics are driving the region's heightened vulnerability.

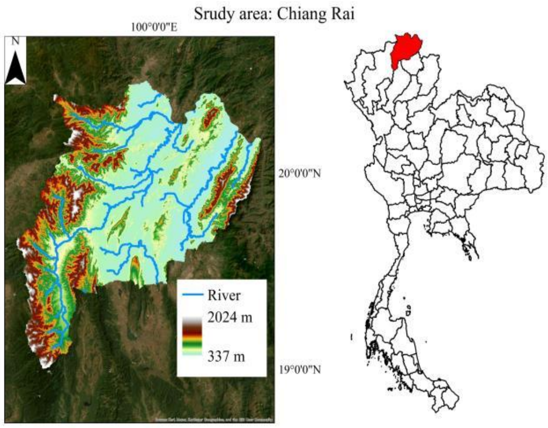

Fig.1 Study area design

4. METHODOLOGY

As shown in Fig. 2, this study adopts an integrated geospatial approach to evaluate flash flood susceptibility under changing land use conditions. The overall methodology consists of five main steps described as follow. First, Land use/land cover (LULC) data of 2007, 2012, and 2018 were obtained and classified to map the spatial distribution of land use categories across Chiang Rai. Next, a high-resolution Digital Elevation Model (DEM) was analyzed to extract slope gradients, representing the terrain's influence on runoff generation. Soil data for the region were then processed to determine Hydrologic Soil Groups (HSGs), which indicate the infiltration capacity of different soil types. Using the land cover and HSG information, Curve Number (CN) values were assigned to quantify runoff potential for each land use-soil combination. Finally, a Flash Flood Potential Index (FFPI) model was implemented by integrating the slope, land use, and soil (CN) datasets to produce a composite flash flood susceptibility map. The following subsections describe each step in detail.

4.1 The Land Use Classification

The Land use data for 2007, 2012, and 2018 were obtained from official Thai government sources. The datasets were classified into agriculture, grassland, road, built-up areas, woodland, water, and bare soil. The land use map for 2007, 2012, and 2018 is presented in Figure 3, illustrating the distribution of major land cover types across Chiang Rai. This land use information provides the basis for analyzing how changes in land cover (e.g. deforestation or urban expansion) might affect runoff and flash flood susceptibility.

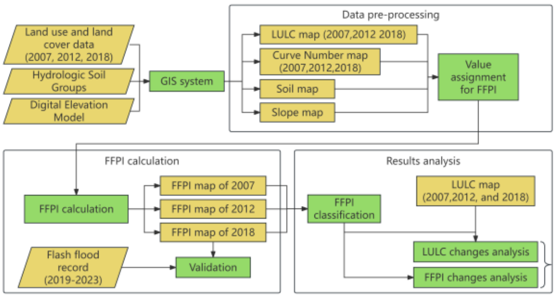

Fig.2 Framework of the methodology

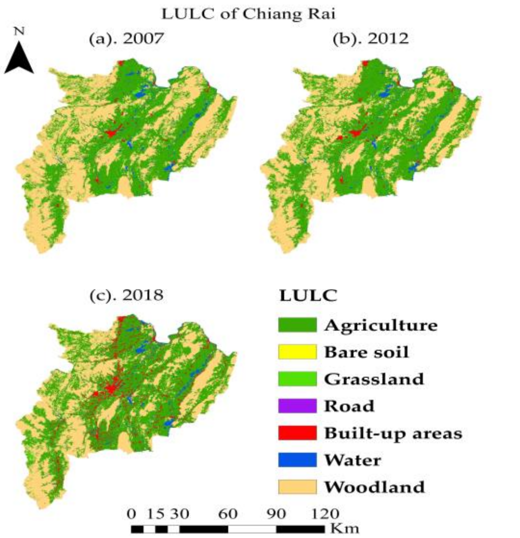

Fig.3 LULC in Chiang Rai (2007, 2012, and 2018)

4.2 Slope Extraction

Topographic slope is a critical factor influencing surface runoff velocity and concentration. In this study, slope values were derived from a DEM of the Chiang Rai region [12]. The Copernicus GLO-30 Digital Elevation Model (DEM) was used to extract slope data across Chiang Rai. Slope plays a critical role in determining runoff accumulation, flow velocity, and erosion potential. The DEM data were processed in a GIS environment to generate a slope map, which was later incorporated into the flash flood potential analysis. Fig 4.(a) showed the distribution of slope in Chiang Rai. This categorized slope layer was then prepared for input into the flash flood susceptibility analysis [16].

4.3 Hydrologic Soil Groups Determination

Soil characteristics were incorporated via the

Hydrologic Soil Group classification, which distinguishes soils by their infiltration capacity [12]. To determine the hydrologic soil types in Chiang Rai, this study utilized the Global Hydrologic Soil Groups (HYSOGs-250m) for Curve Number-Based Runoff Modeling data set [17]. The dominant soil types in the study area were identified and each was assigned to an HSG category (A, B, C, or D) according to its texture and permeability. In general, Group A soils have high infiltration rates and low runoff potential (e.g., sandy or well-drained loams), whereas Group D soils have very low infiltration (high runoff potential, often clayey or shallow soils). Intermediate groups B and C represent moderate and low infiltration capacities, respectively. Figure 4(b) displays the spatial distribution of these HSGs across the study area. Notably, Chiang Rai's soil (Fig 4.(b)) is consist of soil group C and D, indicating a high runoff potential. This HSG layer serves as a crucial input for assessing runoff generation, as it provides a spatial representation of soil-driven infiltration variability [18].

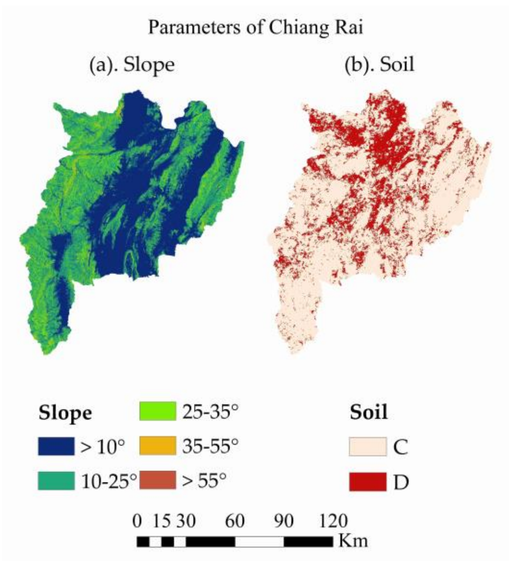

Fig.4 (a).Slope and (b). Hydrologic Soil groups of Chiang Rai

4.4 Curve Number (CN) Assignment and Analysis

The NRCS Curve Number method was employed to quantify the runoff generation potential based on combined land use and soil conditions [12]. Using the land use classification (Fig.3) and the HSG map (Fig.4 (a)), a CN value was assigned to each unique land use – soil group combination in the study area. Standard Curve Number lookup tables developed by the USDA Soil Conservation Service for Antecedent Moisture Condition II guided the assignment [19][20]. For example, forested areas on well-drained Group A soils typically receive a low CN (indicating high infiltration and low runoff potential), whereas urban or paved areas on Group D soils are given a high CN (indicating very high runoff potential). The output of this step was a spatial CN map representing the runoff coefficient across Chiang Rai for 2007, 2012, and 2018, showed in Fig.5. This CN map was examined to understand how land use changes have altered runoff potential over time. Specifically, by comparing CN distributions between the historical and recent land use scenarios, we could identify areas where urban expansion or deforestation has significantly increased runoff susceptibility. The CN analysis thus provides a quantitative link between land cover change and hydrologic response, serving as a foundation for the subsequent flash flood risk modeling.

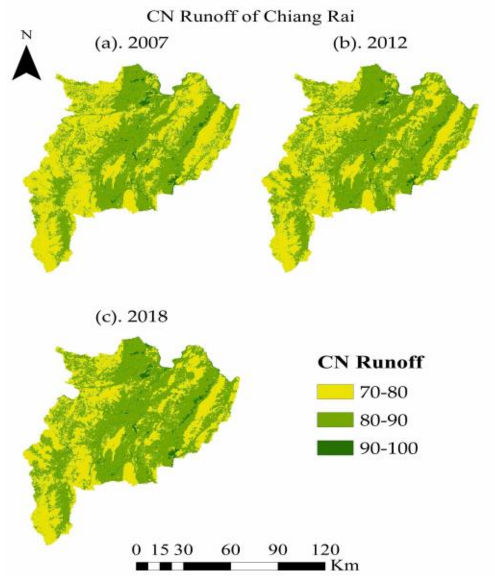

Fig.5 CN runoff in Chiang Rai (2007, 2012, and 2018)

4.5 FFPI Calculation and Classification

The final step involved modeling the Flash Flood Potential Index to delineate areas with high Flash flood susceptibility [12]. The FFPI is a dimensionless index that integrates the key contributory factors-topography, land cover, and soil/infiltration characteristics-into a single susceptibility score for each location. In this study, the FFPI was computed by combining the LULC (Fig.3), slope (Fig.4 (a)), and soil/infiltration information (Fig.4 (b)). Each input parameter was first standardized to an appropriate scale so that higher values correspond to higher flash flood risk. Land use categories were likewise assigned risk scores reflecting their imperviousness or vegetation cover (for instance, urban areas and bare land were given high risk scores, while forested areas were given low scores due to better rainfall absorption). Slope classes and HSGs were converted to rank scores (1 to 10) based on their tendency to generate runoff (with steep slopes and low-infiltration soils receiving higher scores). The CN runoff values were also utilized to inform the weighting of land use and soil contributions, ensuring that areas with high CN (indicative of high runoff potential) are represented as high-risk in the FFPI computation. The integrated FFPI was then calculated on a cell-by-cell basis by combining the factor scores referred to Table 1 [12], effectively averaging or summing the contributions of slope, land cover, and soil.

The final FFPI values were classified into five risk categories:

1.Low (1–3): Areas with minimal runoff and high infiltration capacity.

2.Moderate (3–5): Areas with moderate runoff potential but not highly susceptible to flooding.

3.Medium (5–6): Areas where runoff starts accumulating significantly, increasing the likelihood of flash floods.

4.Elevated (6–8): Areas with high runoff potential and reduced infiltration, making them prone to flash flooding.

5.High (8–10): Severely flood-prone areas with rapid surface runoff and minimal infiltration, where flash floods are most likely to occur.

Table 1. The weighted contribution of each parameters and the ranks of each parameters category [12]

Layer	Weight	Category	Rank
Slope	40	< 10°	1
		10°-25°	3
		25°-35°	5
		35°-55°	8
		> 55°	10
Soil	20	C	7
		D	10
LULC	20	Woodland	5
		Bare soil	3
		Built up	9
		Roads	9
		Agriculture	7
		Grassland	7
		Water	4
CN runoff	20	70-80	8
		80-90	9
		90-100	10

5. RESULTS

5.1 FFPI Distribution in Chiang Rai (2007, 2012, and 2018)

Fig.5 illustrates the spatial distribution of the Flash Flood Potential Index (FFPI) across Chiang Rai for 2007, 2012, and 2018. Notably, no areas in the province fell into the “Low” FFPI category during this period. Instead, the entire landscape was classified within the Moderate, Medium, Elevated, or High risk classes, indicating a generally elevated baseline of flash flood susceptibility throughout Chiang Rai. The Medium FFPI category covered the majority of the area in all three years, followed by the Moderate category, whereas Elevated-risk zones constituted a much smaller fraction of the area, and High-risk zones were extremely limited (consistently <0.1% of the province’s area in each year). This absence of Low-risk areas and dominance of at least Moderate FFPI values suggest that most of Chiang Rai had non-trivial flash flood susceptibility.

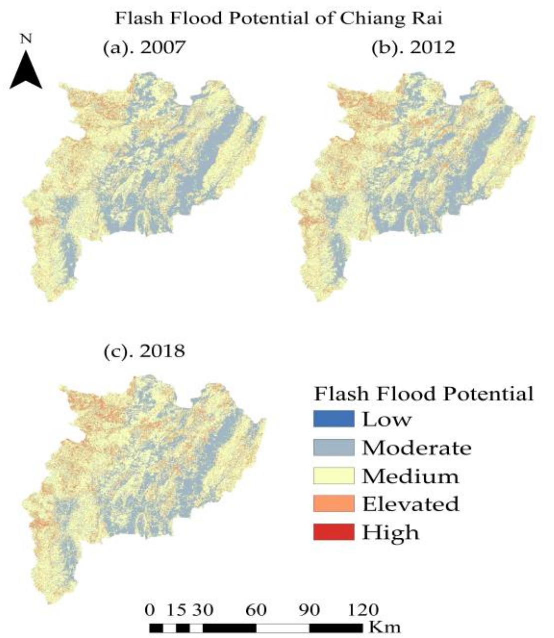

Fig.6 The FFPI results in Chiang Rai (2007, 2012, and 2018)

5.1.1 Relationship between FFPI and flash flood records

To validate the ability of the FFPI distributions to reflect local flash flood conditions in Chiang Rai, recorded flash flood events from 2019 to 2023 were compared with the 2018 FFPI map at the sub-district level. In the absence of detailed inundation extents or depth measurements, the analysis employed the count of severe flash flood occurrences per sub-district. Fig.7 illustrates the spatial correspondence between event frequency and 2018 FFPI values, revealing a concentration of higher flash flood frequency in the regions where elevated and medium FFPI values are more concentrated. The higher number of events within a given period indicates the elevated flood risk [2], this spatial clustering supports the predictive capability of FFPI. Collectively, this comparison indicated that the FFPI can meaningfully approximate the temporal and spatial patterns of flash floods in Chiang Rai.

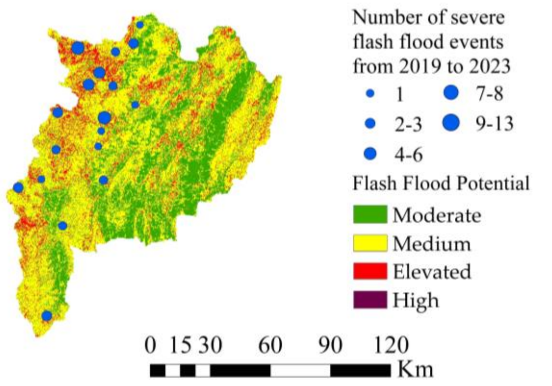

Fig.7 Number of flash flood events during 2019 to 2023 in Chiang Rai

5.2 Relationship between FFPI Distribution Changes and Land Use/Land Cover Changes

5.2.1 Overall FFPI trends

The region's FFPI distribution shifted toward higher risk categories over time, as showed in Fig.8. Across the entire province, the area classified as High FFPI increased substantially, while Elevated-risk areas also expanded, especially by 2018. In contrast, Moderate-risk zones shrank continuously, and Medium-risk areas fluctuated (slightly decreasing from 2007 to 2012, then increasing by 2018).

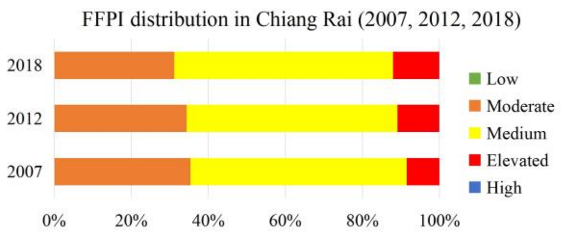

Fig.8 The FFPI distributions in Chiang Rai (2007, 2012, and 2018)

According to Table 2, during the initial 2007-2012 period, changes were modest. For example, the total area under High FFPI rose by only about 55.5% relative to 2007, and Elevated by 28.3%, whereas Medium and Moderate categories saw small declines (around -2.5% each). However, in the subsequent 2012–2018 interval a more pronounced escalation in risk occurred: High FFPI area grew by an additional 17.8%, and Elevated by 10.0% (relative to 2012 values), while Medium-risk area rebounded by 3.9% and Moderate continued to decline by -9.3%. The net result by 2018 was a greater proportion of the landscape in the High and Elevated categories than in 2007. These trends underscore an overall increase in flash flood susceptibility in Chiang Rai between 2007 and 2018, pointing to underlying drivers that intensified flood potential over time.

Table 2. Changes in FFPI category coverage across Chiang Rai

FFPI Category	Change in Area (2007–2012)	Change in Area (2012–2018)
High	+55.45%	+17.83%
Elevated	+28.29%	+10.01%
Medium	-2.53%	+3.87%
Moderate	-2.86%	-9.25%

5.2.2 FFPI changes in urban areas

When focusing on urbanized areas (built-up land and roads), the FFPI shifts were even more concentrated and extreme. Table 3 shows that in areas of urban growth, higher-risk FFPI classes expanded dramatically, especially during 2012 – 2018. In that period, the area classified as High FFPI in urban regions increased fivefold (approx. +500%), while Elevated-risk urban areas tripled (+208%), and Medium-risk urban areas nearly quadrupled (+296%). By contrast, from 2007 to 2012 the urban FFPI changes were minimal – High-risk urban area remained effectively unchanged (0% increase), and only modest growth occurred in the Elevated (+26%) and Medium (+21%) categories. The sharp rise in High and Elevated FFPI within urban and peri-urban zones after 2012 indicates that rapid urban expansion considerably intensified local flash flood potential. In other words, new development has been occurring in, or contributing to, areas of higher inherent flood risk, raising concern for those urbanizing locales.

Table 3. Changes in FFPI category coverage in Urban areas of Chiang Rai

FFPI Category	Change in Area (2007–2012)	Change in Area (2012–2018)
High	0.00%	+500.00%
Elevated	+26.23%	+207.82%
Medium	+21.18%	+295.61%

5.2.3 Land use/Land cover (LULC) change linkages

The observed FFPI increases are closely linked to major land use transitions in Chiang Rai over the study period. The extensive LULC changes by area are showed in Fig.9. Between 2007 and 2012, the largest transition was the conversion of approximately 754.58 km^2 of woodland to agricultural land. Replacing forest cover with agriculture tends to increase runoff and flash flood potential. This woodland-to-agriculture conversion corresponds with the moderate rise in Elevated FFPI areas observed in 2007-2012. In the 2012-2018 period, the dominant change was urban expansion: about 437.87 km^2 of agricultural land was transformed into urban/built-up use (including road networks). This extensive agriculture-to-urban conversion greatly reduced infiltration and further increases runoff, aligning with the marked surge in High and Elevated FFPI areas after 2012. Another major change was an additional 407.01 km^2 of woodlands (intact through 2012) being converted to agriculture by 2018, reinforcing the pattern of deforestation contributing to flood hazard. Overall, these land use changes explain the FFPI distribution shifts: early-stage deforestation for agriculture created conditions for higher runoff (elevating flood risk), and subsequent urbanization of farmland amplified that effect, leading to a notable increase in high flash-flood-susceptibility zones across Chiang Rai by 2018.

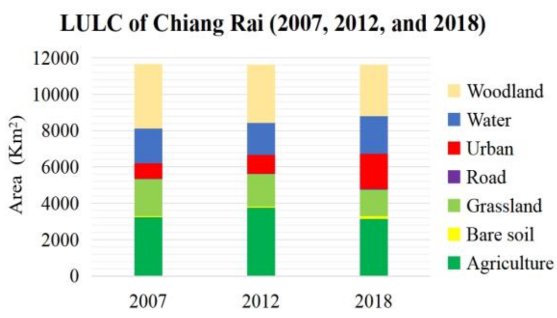

Fig.9 Proportions of the major LULC in Chiang Rai (2007, 2012, and 2018)

6. CONCLUSIONS

The comprehensive assessment of flash flood susceptibility in Chiang Rai Province revealed a critical lack of "Low" risk zones, with the entire landscape classified as either Moderate or High risk. Temporal analysis highlighted a distinct trend of escalating flash flood potential, particularly during the 2012–2018 interval. While the increased risk observed from 2007 to 2012 was primarily attributed to the conversion of woodland to agricultural land, the subsequent period (2012-2018) witnessed a sharp surge in high-risk zones driven largely by the urbanization of agricultural areas. Specifically, this rapid urban expansion resulted in a fivefold (+500%) increase in high Flash Flood Potential Index (FFPI) zones within built-up areas, demonstrating that land-use transitions act as the primary accelerator of flood susceptibility.

These findings were further reinforced by validation against actual flood records from 2019 to 2023, which confirmed a strong correlation between the identified High/Moderate FFPI zones and the frequency of flash flood events. Spatially, sub-districts in western Chiang Rai, characterized by steeper slopes, exhibited consistently higher FFPI values compared to the lower-gradient eastern lowlands. This is particularly critical where urban sprawl has encroached upon steep terrain-a synergistic combination that significantly accelerates surface runoff and minimizes infiltration time, thereby amplifying the intensity and sudden onset of flash floods.

From an exposure perspective, the expansion of urban areas into Elevated and High risk areas has inherently increased the susceptibility of human communities to flash flood impacts. Concurrently, ongoing deforestation further exacerbated surface runoff formation during rainfall events, directly heightening community flash flood vulnerability.

On the other hand, except the passive monitoring, effective disaster management may also be necessary. Rigorous land-use planning in high-slope regions is essential to prevent further exposure of communities to high-risk zones. Simultaneously, targeted flood-control infrastructure, such as check dams designed to retard runoff velocity, should be implemented in identified flash flood hotspots to mitigate hazards and protect at-risk populations.

In conclusion, this study utilized the FFPI framework integrated with multi-temporal land-use data to characterize flash flood risks in Chiang Rai, Thailand. The results demonstrated a clear temporal escalation in flash flood risk driven by land-use changes: urbanization has increased community exposure, while deforestation has heightened vulnerability to flash flood hazards. Based on this, effective management like flood control facilities implement and better land-use management policy are recommended.

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